# Document Classification: Part I

Statistical Analysis and Document Mining

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# Outline

# Introduction

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  *Spam detection*: given a letter, recognize it is a spam or not.

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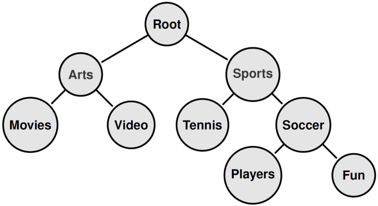
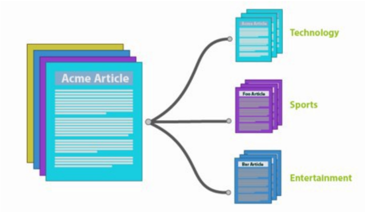
- In many scenarios, we observe text data:
  *Genre classification*: automatically classify articles by genre.



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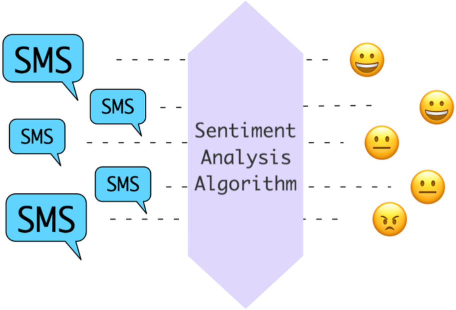
- In many scenarios, we observe text data:
  *Sentiment analysis*: determine emotions of the writer.



# Introduction

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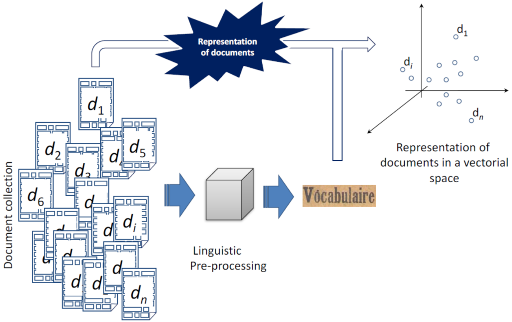
- In many scenarios, we observe text data:
  *Language identification*: recognize the language of the text.


- Our observations are labeled raw documents. Before learning, we have to process text first to get "numbers".
- By linguistic preprocessing we distinguish unique words (*terms*) that form our *vocabulary*.
- Using some rule, we represent data in a feature space. Usually, each feature is a word with values indicating its importance.



# Outline

# Segmentation

- *Segmentation* (tokenization): separate a sequence of characters into semantic elements, or *words*.
- *Term* (type of words): class of all words having the same sequence of characters.
- *Example*:

  *"The cat sat on the mat."*

  *Words*: The, cat, sat, on, the, mat

  *Terms*: the, cat, sat, on, mat
- *Dificulty*: Tokenization is language specific.

# Example: Segmentation In French

In French, the following issues may arise during the segmentation process:

- Lexical components with hyphens:
  *chassé-croisé, peut-être, rendez-vous*
- Lexical components with an apostrophe:
  *jusqu'où, aujourd'hui, prud'homme*
- Idiomatic expressions:
  *au fait, poser un lapin, tomber dans les pommes*
- Contracted forms:
  *j', M'sieur, Gad'zarts (les gars des Arts et Métiers)*
- Acronyms:
  *K7, A.R., CV, càd, P.-V.*

# Normalization

1. *Textual normalization*: consists in reducing the words of a same family to their canonical forms.
   - Punctuation: suppression of points and hyphens;
   - Lower-upper case: transform all upper cases to lower cases;
   - Accents: suppression of accents.

2. *Linguistic normalization* consists in
   - Rooting: replace each word by its root;
   - Stemming: replace each word by its canonical form.

# Examples of Preprocessing

## Non-spam message before prepocessing

Subject: Re: 5.1344 Native speaker intuitions The discussion on native speaker

intuitions has been extremely interesting, but I worry that my brief intervention may have muddied the waters. I take it that there are a number of separable issues. The first is the extent to which a native speaker is likely to judge a lexical string as grammatical or ungrammatical per se. The second is concerned with the relationships between syntax and interpretation (although even here the distinction may not be entirely clear cut).

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# Preprocessed Documents from Different Classes

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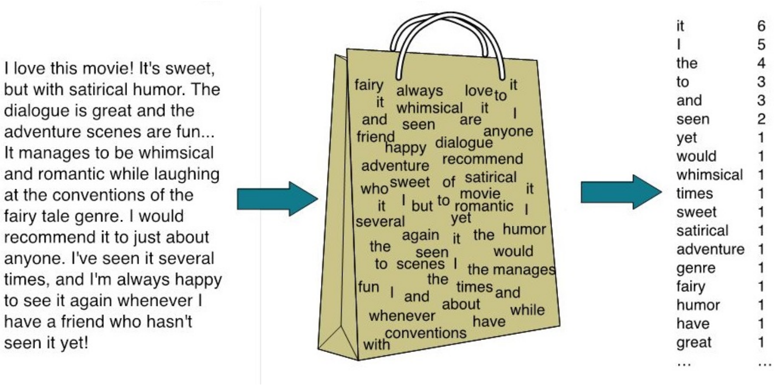
## Spam message after prepocessing

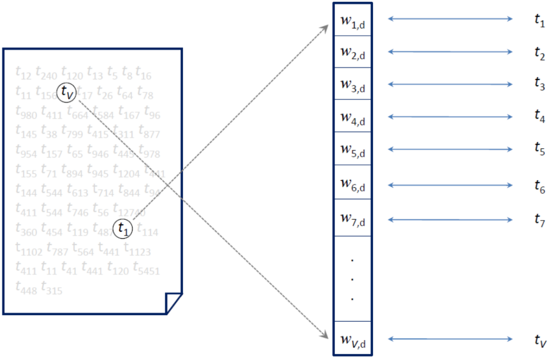
**financial freedom** follow financial freedom work ethic extraordinary desire **earn** least per month work home special skills experience required train personal support need ensure success legitimate homebased **income opportunity** put back control finance life ve try opportunity past fail live **promise**

- The idea of the bag-of-words is to take simply into account only the word appearances ignoring the word order in a sentence (like if we put all words in a bag).



# Vector Space Model (Salton & Lesk, 1965)

- Given a document, we assign to each term $t_j$ a specific value $w_{j,d}$. Then, a document is represented as a vector: $\mathbf{d} = (w_{j,d})_{j=1}^{V}$.
- How we define importance $w_{j,d},\ j \in \{1, \ldots, V\}$?



# Binary and Term Frequency (TF) Rules

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- *Problem:* Need to store a matrix of size $n \cdot V$.
  - What is approximately the size of a data set in GB, if $n = 200,000$, $V = 10,000$ and one entry needs 8 bytes?
  - Around 16 GB!

# French Wikipedia Collection: Statistics

| Variables | Values |
| --- | --- |
| **# of documents in the collection** | **1,349,539** |
| Total # of occurrences of words | 696,668,157 |
| Average # of words per document | 416 |
| Size of the pre-processed collection on the disk | 4.6 GB |
| Total # of types of words | 757,476 |
| Total # of types of words after rooting | 604,244 |
| **Size of the vocabulary** | **604,244** |
| **Average # of terms per document** | **225** |
| Size of the collection after removing a stop-list | 2.8 GB |

- From the statistics, we can see that the number of features in the bag-of-words will be $604,244$, but, in average, only $225$ of them will not be equal to $0$ for each document.

- Hence, we deal with *sparse matrices*: most of entries are zeros.

- To reduce the storage overhead, we can store data in a sparse format by keeping non-zero elements only.

The *CSR format* stores a matrix $(n \times V)$, where $NNZ$ entries are not zero, as 3 one-dimensional arrays $Val, CI, RI$.

- $Val$ stores all non-zero entries.
- $CI$ stores their column indices, so the size of $CI$ is also $NNZ$.
- $RI$ stores cumulatively the number of non-zero entries per row. The size of $RI$ is $n+1$. $RI[1] = 0,\ RI[n+1] = NNZ$. To get the number of non-zero entries for row $i$, we compute $RI[i+1] - RI[i]$.

# LibSVM Format

- In machine learning, it is popular to store a data set in the *LibSVM format*.
- The data is stored as a 2d array, in which rows may have different number of columns.
- For each row, the first element is the class label, and the rest are *column-index:value* pairs that correspond to non-zero entries.

| y | index-value | | index-value |
|---|---|---|---|
| 2 | 5:0.356 | ... | 9:1000 |
| 3 | 2:10.2 | ... | 15:0.01 |

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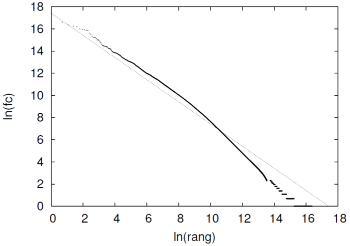
- When the collection was filtered by removing a stop-list ("a", "the", "of", etc.) of size 200 words, the average number of terms was reduced in documents from 416 to 225 (around 45% reduction). Why?
  In addition, their filtering reduces the space on the disk of about 39% (from 4.6 GB to 2.8 GB).

*The number of occurrences $fc(word)$ of a word $word$ in a document collection is inversely proportional to its rank:*

$$\forall word: \quad fc(word) \approx \frac{\lambda}{\text{rang}(word)}.$$

$\Rightarrow$ The k-th most frequent word is approximately k times less present than the most frequent one.




| Rank | Word | Freq. | % |
|---|---|---|---|
| 1 | the | 22,038,615 | 4.9% |
| 2 | be | 12,545,825 | 2.79% |
| 3 | and | 10,741,073 | 2.39% |
| 4 | of | 10,343,885 | 2.3% |
| 5 | a | 10,144,200 | 2.25% |
| 6 | in | 6,996,437 | 1.56% |
| 7 | to (i.m.) | 6,332,195 | 1.41% |
| 8 | have | 4,303,955 | 0.96% |
| 9 | to (p.) | 3,856,916 | 0.86% |
| 10 | it | 3,872,477 | 0.86% |

Top 10 frequent word from the 450 million word corpus (`https://www.wordfrequency.info`).

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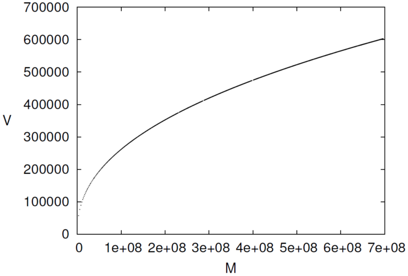
- How many frequent words we should suppress?
  - We should be aware that removing of too many words may harm prediction performance. Usually, modern packages have tools to remove stop-list words of most spoken languages.

*The size of the vocabulary $V$ increases sub-linearly with respect to the total number of words $M$ present in a collection:*

$$V = k \cdot M^{\beta},$$

where $k$ and $\beta$ are parameters that are dependent on the collection. Typically, in English text corpora $k \in [10, 100]$, and $\beta \in [0.4, 0.6]$.

$\Rightarrow$ Larger the collection size, larger the vocabulary size.



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- However, less frequent terms can also have large importance, since they can be class-specific.

  *Example:* Medical Prescription vs Recipe.

| take | water | glass | eat | wait | ... | paracetamol | sugar | stomach |
|---|---|---|---|---|---|---|---|---|
| 7 | 6 | 4 | 4 | 4 | ... | 0 | 2 | 0 |
| 6 | 7 | 4 | 3 | 5 | ... | 1 | 0 | 1 |

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- We want to take into account document frequency of terms by diminishing the weight of terms that occur frequently across documents and increasing the weight of terms that occur rarely in average.

# TF-IDF Weighting Rule

The TF-IDF rule is a trade-off between term frequency and document frequency:

- Normalized term frequency (tf part):

$$\frac{\mathrm{tf}_{t_j,d}}{\sum_{j=1}^{V} \mathrm{tf}_{t_j,d}} = \frac{\mathrm{tf}_{t_j,d}}{N_d}.$$

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- Then, the tf-idf weight is defined as:

$$w_{t_j,d} = \frac{\mathrm{tf}_{t_j,d}}{N_d} \ln \frac{n}{\mathrm{df}_{t_j}}.$$