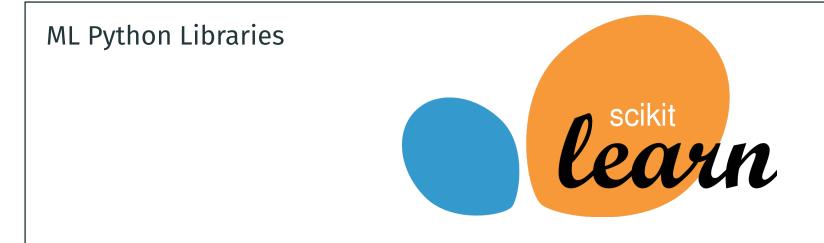


TEXT CLEANING & VECTORISATION

IA FRAMEWORKS

GOOGLE CLOUD PLATFORM





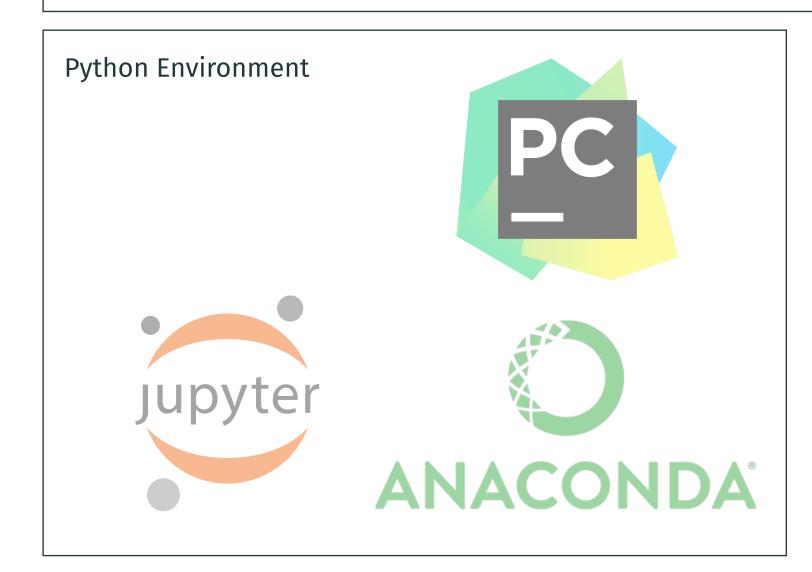














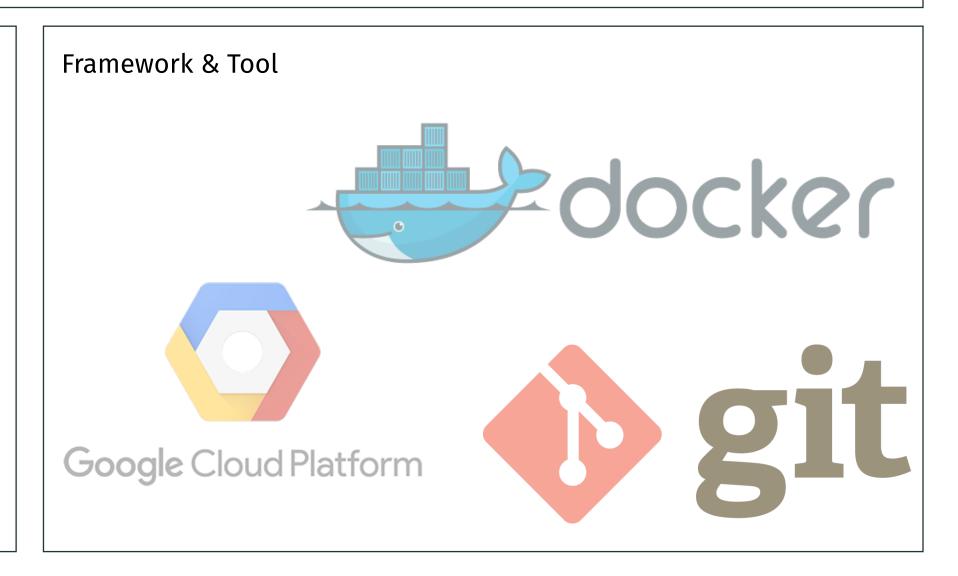


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INTRODUCTION

TEXT USE CASE IN ARTIFICIAL INTELLIGENCE

There are multiple applications of artificial intelligence on text data:

- Information retrieval: on text or content-based (Google, Yahoo etc.)
- PATTERN RECOGNITION: Information/Named extraction.
- SENTIMENT ANALYSIS: Marketing. Website comments.
- Text generation: Chatbot. Newspaper article.
- TEXT TRANSLATION: Google Translate. DeepL.
- **DISAMBIGUATION**: Security.
- And many others...

Text processing does not always mean Natural Language Processing (NLP)

EXAMPLE: TEXT CLASSIFICATION

OBJECTIVE: Automate the categorisation of text product within discount website. Data come from datascience contest <u>website</u>.

DIFFICULTIES:

- Text data require processing to used machine learning model on it.
- Big amount of data (15M of text description).
- Highly unbalanced classes.
- High number of classes (more than 5000).
- Real dataset that requires a lot of cleaning.

DATA

Train file contains 15.786.885 products. Answer of test file not furnished.

Three levels classification:

- 47 categories of level 1.
- 536 categories of level 2.
- 5789 categories of level 3.

Field	Туре	Description
product id	String	Unique identifiant du produit
Catégorie 1	String	Catégorie de niveau 1
Catégorie 2	String	Catégorie de niveau 2
Catégorie 3	String	Catégorie de niveau 3
Description	String	Description produit
Libelle	String	Description courte
Marque	String	Marque du produit

DATA EXAMPLE

Categorie1	
ANIMALERIE - NEW	Lit Mijou, 48 × 37 Pouces, Crèmeimitation
ARME DE COMBAT - ARME DE SPORT	Réplique chargeur STI DUTY ONE (CPG1945) - Rép
ART DE LA TABLE - ARTICLES CULINAIRES	Mugs Alchemy (king 13) (Taille unique) - Mugs
ARTICLES POUR FUMEUR	E-PACK FRUITÉ 'EXPERT' (Titanium bleu - Mixte
AUTO - MOTO (NEW)	Tube de fourche Tarozzi KYMCO X-CITING 500 - 0
BAGAGERIE	portefeuille porte cartes billets compagnon fe
BATEAU MOTEUR - VOILIER	Echelle pour plateforme70086 - Fabrication i
BIJOUX - LUNETTES - MONTRES	Seiko SFP599 Hommes Montre - Acheter Authentiq
BRICOLAGE - OUTILLAGE - QUINCAILLERIE	Clé polygonale double contre-coudée - 20x22
CHAUSSURES - ACCESSOIRES	Bottes bi-matière à talons bleu - Zaza Pata
CONDITIONNEMENT	EMBALLAGE Ruban adhésif d'emballage PVC colle
CULTURE / JEUX	De Keenen Ivory Wayans avec Shannon Elizabeth,
DECO - LINGE - LUMINAIRE	Cars Poster Reproduction Sur Toile, Tendue Sur
DROGUERIE (NEW)	PERCHE TELESCOPIQUE SECURITY LOCK 3X2M - PERCH
ELECTROMENAGER	Filtre metal antigraisse (x1) AD546BE11 AD546W
ELECTRONIQUE	Bloc de jonction à fusible Contenu: 20 pc(s) p
EPICERIE	Sel de Guérande aux épices, Verrine 150 gr - S
HYGIENE - BEAUTE - PARFUM	Uriage AquaPRÉCIS Crème Confort 40 ml - Les mi
INFORMATIQUE	Batterie Acer Aspire One 751H-52Yr - Li-Ion 11

DIFFICULTIES

- Noise linked to spelling, grammar, conjugaison mistake.
- Non significant terms.
- Mining of terms depends of context. (Clothes / Dolls' clothes)
- Different from one language to another.
- Transcription to machine learning.

Implies a lot of cleaning.

TEXT CLEANING

STEMMING

PROBLEM: Term can be written in different way (accentuation, genre, conjugaison, plurals, etc.) but still have the same meaning.

SOLUTION: replace word with their stems.

EXAMPLE:

- •Épée, épee, épées, épée = epe
- vert, verts, vertes, vertes = vert
- mange, manger, mangez, mangent, = mang

Algorithm that generate steming from words are rules-based and depends of the language.

The one used on nltk for French language is the Snowball algorithm.

STOPWORDS

PROBLEM: Terms that are very common does not help to classify data and can even disturb the training.

SOLUTION: Most common words are removed. This words are called stopword.

EXAMPLE:

- FRENCH: 'au', 'aux', 'avec', 'ce', 'ces', 'dans', 'de', 'des', 'du', 'elle', 'en', 'et', 'eux', 'il', 'ils', 'je', 'la', 'le', 'les', 'leur', 'lui', 'ma', 'mais', 'me', 'même', 'mes', 'moi', 'mon', etc.
- ENGLISH: ['i', 'me', 'my', 'myself', 'we', 'our', 'ours', 'ourselves', 'you', "you're", "you've", "you'll", "you'd", 'your', 'yours', 'yourself', 'yourselves', 'he', 'him', etc.

OTHER CLEAN STEPS

- Remove punctuation, number or other non-letter symbol.
- Increment stopwords list with domain words.
- Removed technical noise (HTML code).
- Lower case.

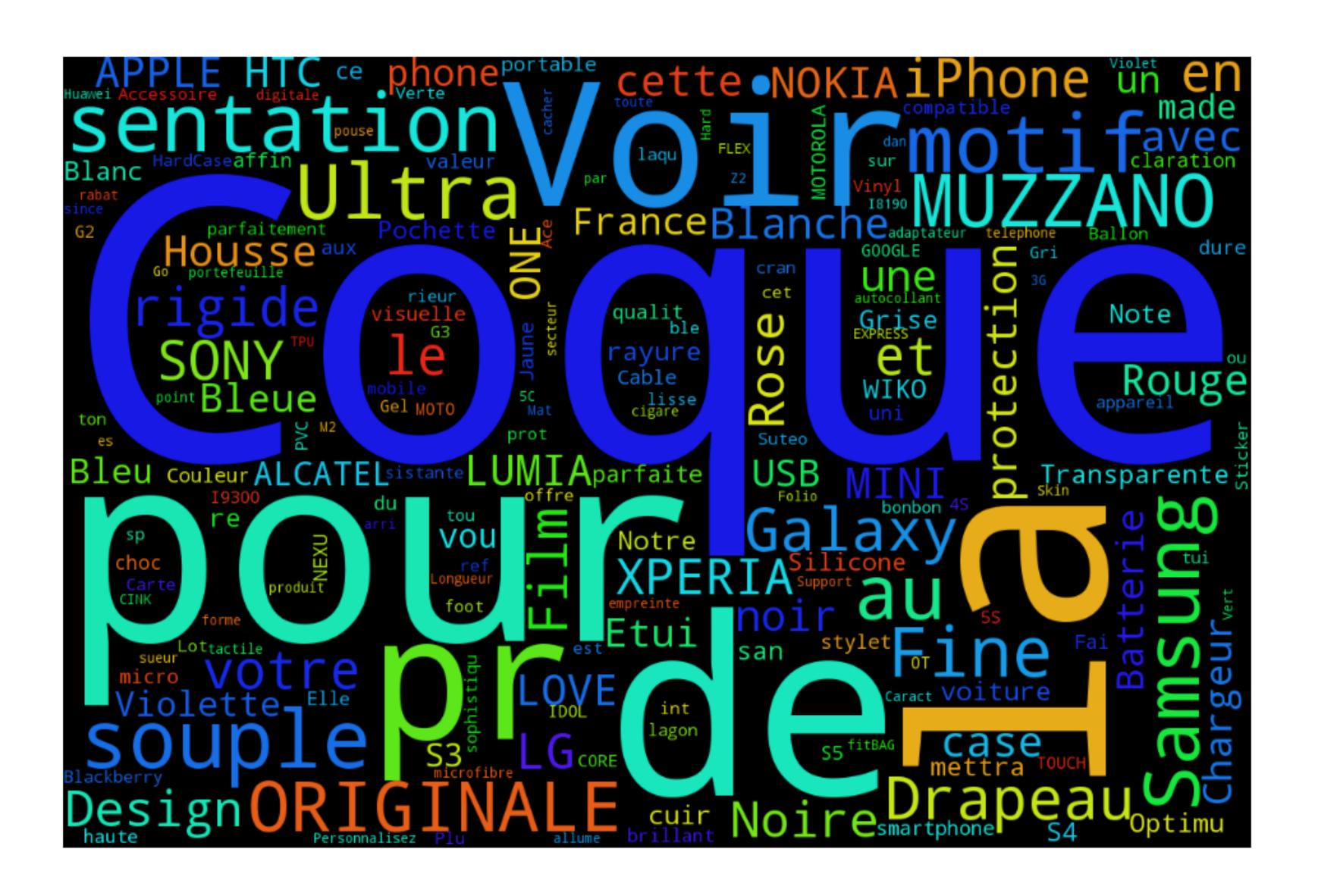
Most of these steps depend of the objectives you want to achieve.

EXAMPLE:

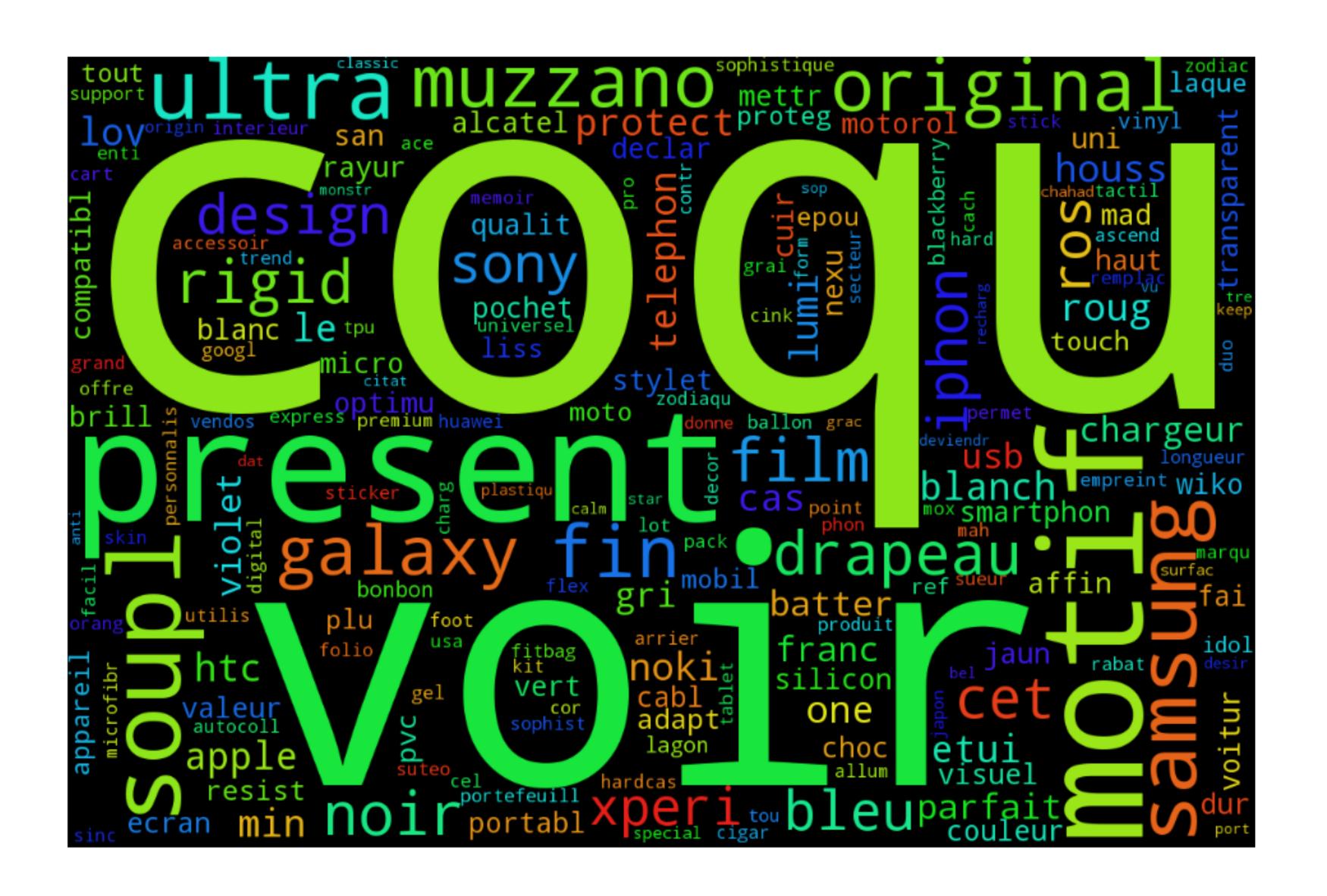
- Upper case can be kept for sentiment analysis.
- Cdiscount: Number can be removed for categorie 1's level and not categories 2 (xbox 360).
- etc.

REGULAR EXPRESSION

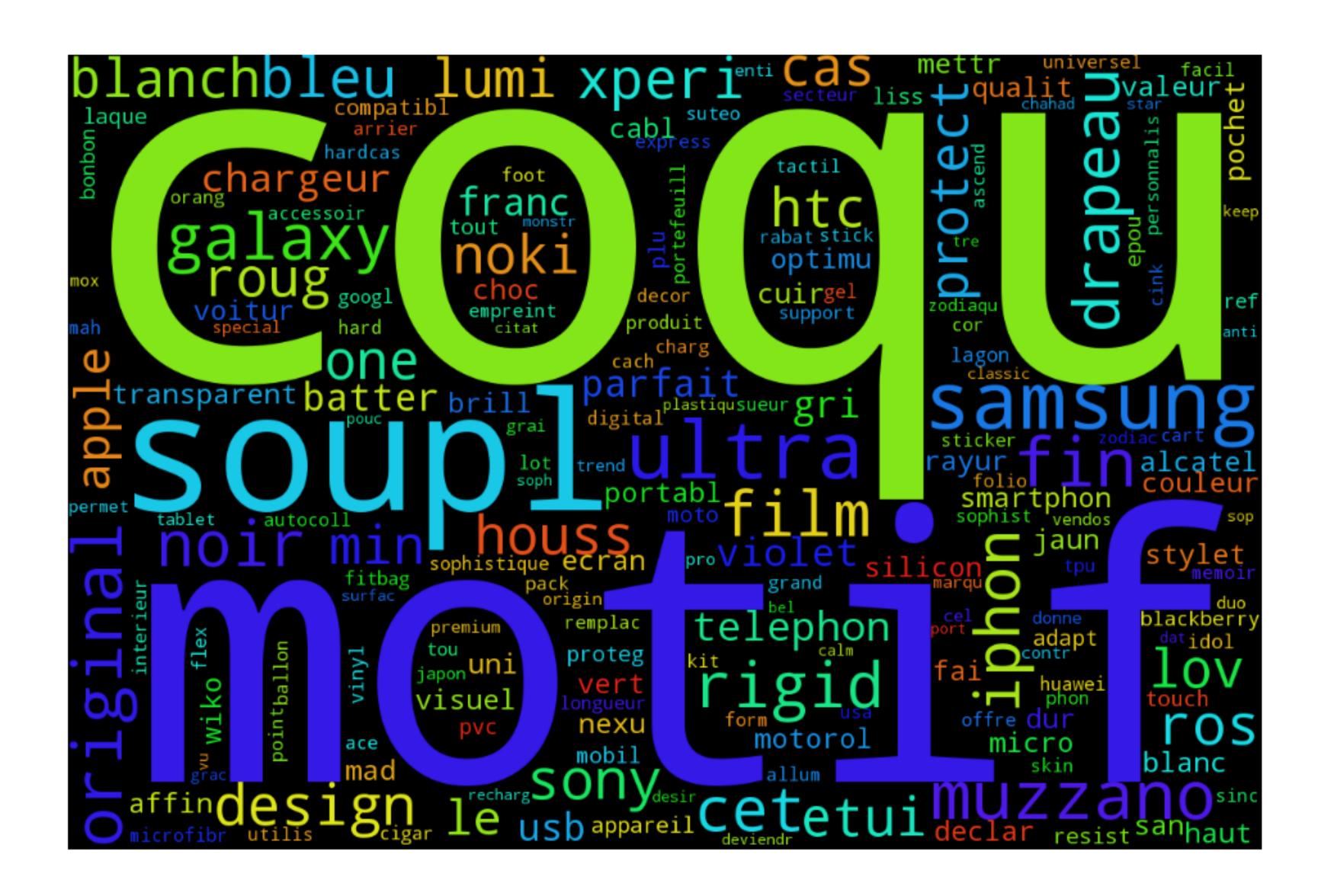
Stopword - Category - "Téléphonie - GPS"



Stopword - Category - "Téléphonie - GPS"



Stopword - Category - "Téléphonie - GPS"



LIBRARIES FOR TEXT PROCESSING

- NLTK (python): language processing (steming, stop words)
- Lucene (java): text indexation and information retrieval
- BeautifulSoup: clean html text.

VECTORISATION

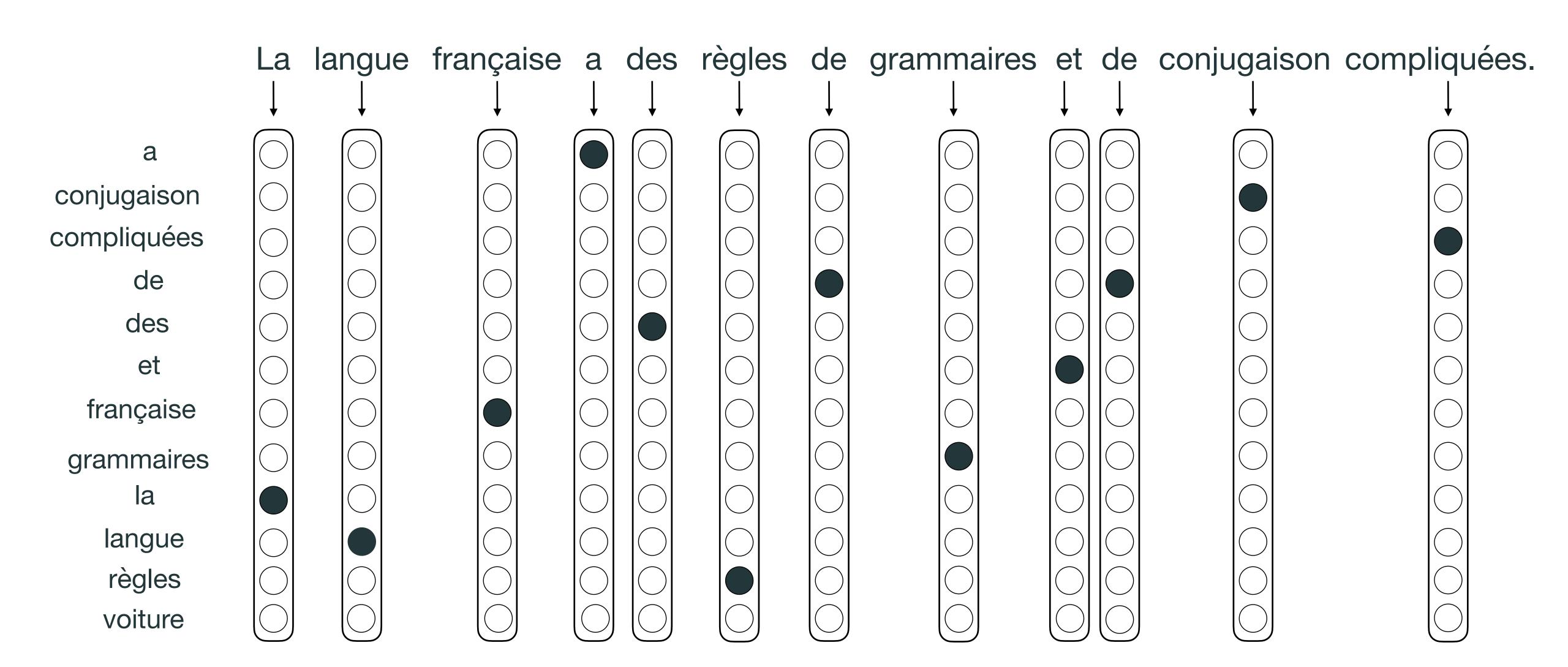
OBJECTIVES AND DIFFICULTIES

- Transform text to numerical data to be used in Al algorithms.
- Manage high number of features. Example:
 - 21.543 lines on category "TELEPHONIE GPS"
 - 24.486 unique words -> 8384 after cleaning.
- Choose significatif words

Two types of solutions:

- Frequency based : Vectorizer
- Learning based: Word Embedding (See corresponding course).

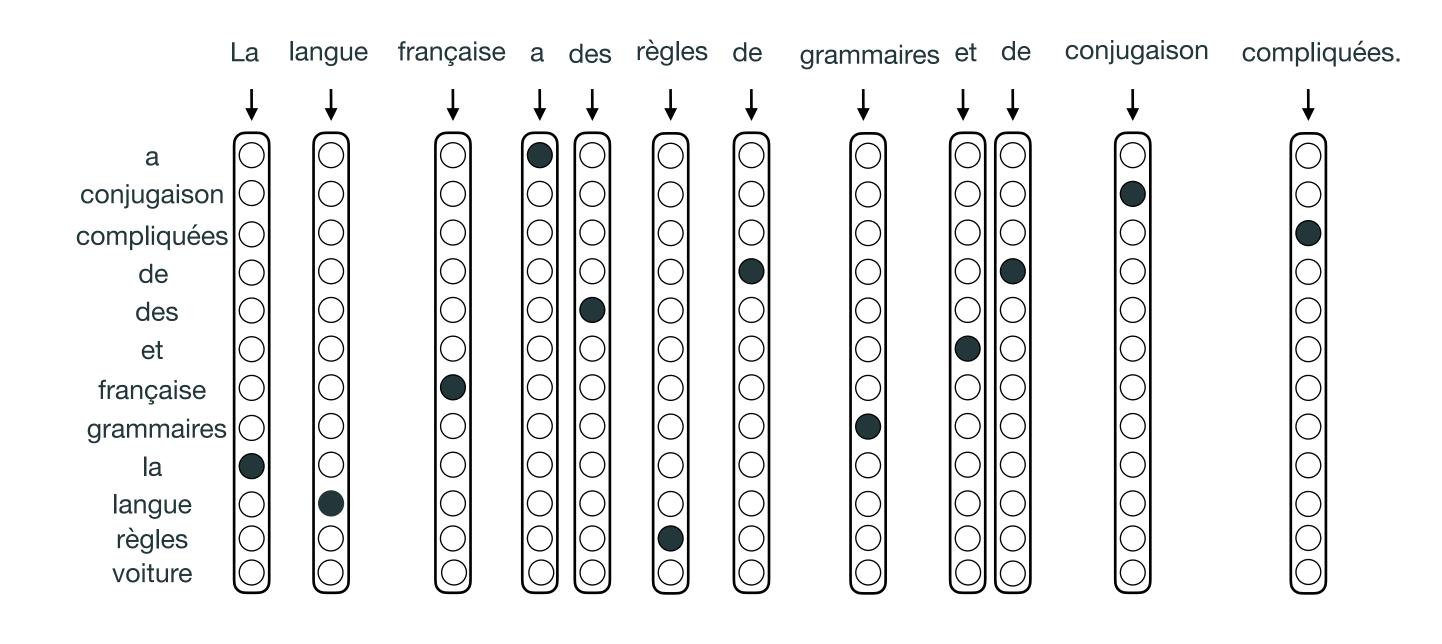
ONE-HOT-ENCODER



Dictionary size: V = 12

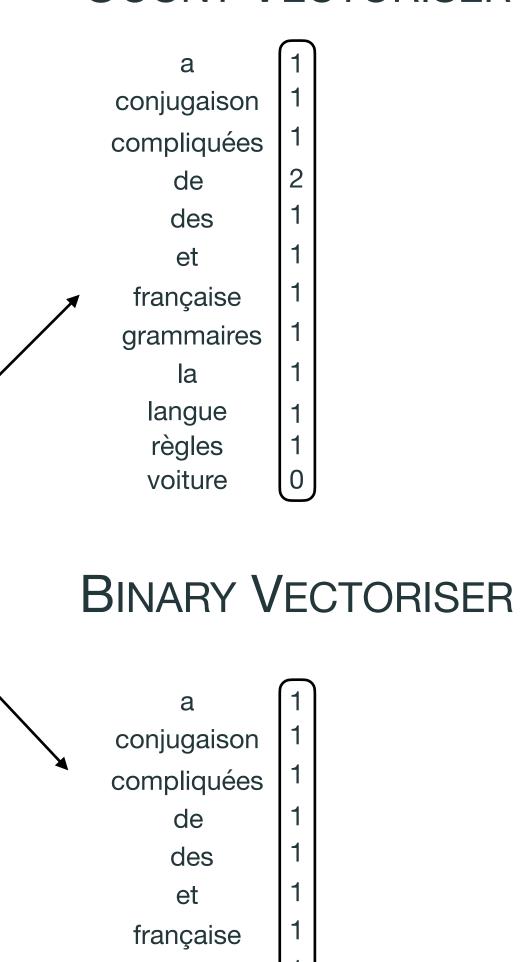
COUNT & BINARY VECTORISER

How to convert OHE encoding to 'sentences' encoding?



Limitation: all words have the same weights





grammaires la langue règles voiture

TF-IDF

Assign a weight to word, a token or an association of words in a document regarding to a corpus of document.

- t: a word or and association of words.
- d: a document.
- D: a corpus of document.

DEFINITION: TF-IDF general formula.

$$tfidf(t, d) = tf(t, d) \times idf(t, D)$$

- tf(t, d): Term-Frequency. Number of occurence of token t in document d.
- idf(t, D): Inverse-Document-Frequency. Importance of token t in the corpus D.

TF FORMULA

The tf(t, d) general formula is defined as the number of occurence t in document d.

$$tf(t,d) = f_{t,d}$$

This definition is used in scikit-learn python library and MILib spark library.

However there exist some variations:

Binary	0,1
Logarithmique normalisation	$1 + log(f_{t,d})$
max normalisation	$0.\mathbf{K} + \mathbf{K}.5 \times \frac{f_{t}f_{d},d}{m_{t}x_{\text{etc}}f_{t}f_{d},d}$
max normalisation (0.5)	$0.5 + 0.5 \times \frac{f_{t,d}}{max_{t' \in d} f_{t',d}}$

IDF FORMULA

The *idf(t, D)* change from an implementation to another.

$log(\frac{N_D}{DF(t,D)})$	
$log(\frac{N_D + 1}{DF(t, D) + 1})$	MILib (Spark)
$log(\frac{N_D + 1}{DF(t, D) + 1}) + 1$	Scikit-learn (Python)

- $\cdot N_D$: Number of documents.
- •DF(t,D): Number of documents in which terms t appears.

DIMENSION ISSUE

BINARY VECTORISER

BINARY VECTORISER

a conjugaison compliquées de de des et 1 française grammaires la 1 langue règles voiture

V=11



- Vectors are very big
- Dimensions gros quickly

HASHING [WEINBERGER AND AL, 2009]

Vectorise descriptions while reduce features space

$$X \longrightarrow \phi$$

Vector of size V, unknown until computing all vocabulary.

Vector of size n_{hash} fixed.

- Determinist function.
- Only one pass on data to build the vector.
- •Unbiased cross product: $\mathbb{E}[\langle \phi(x), \phi(x') \rangle] = \langle x, x' \rangle$

HASHING [WEINBERGER AND AL, 2009]

HASHED FEATURE MAP

$$\phi_j^{\xi,h}(x) = \sum_{i \text{ s.t } h(i)=j} \xi(i)x_i$$

Where

$$h: \mathbb{N} \to \{1,...,nhash\}$$

$$i \mapsto j = h(i)$$

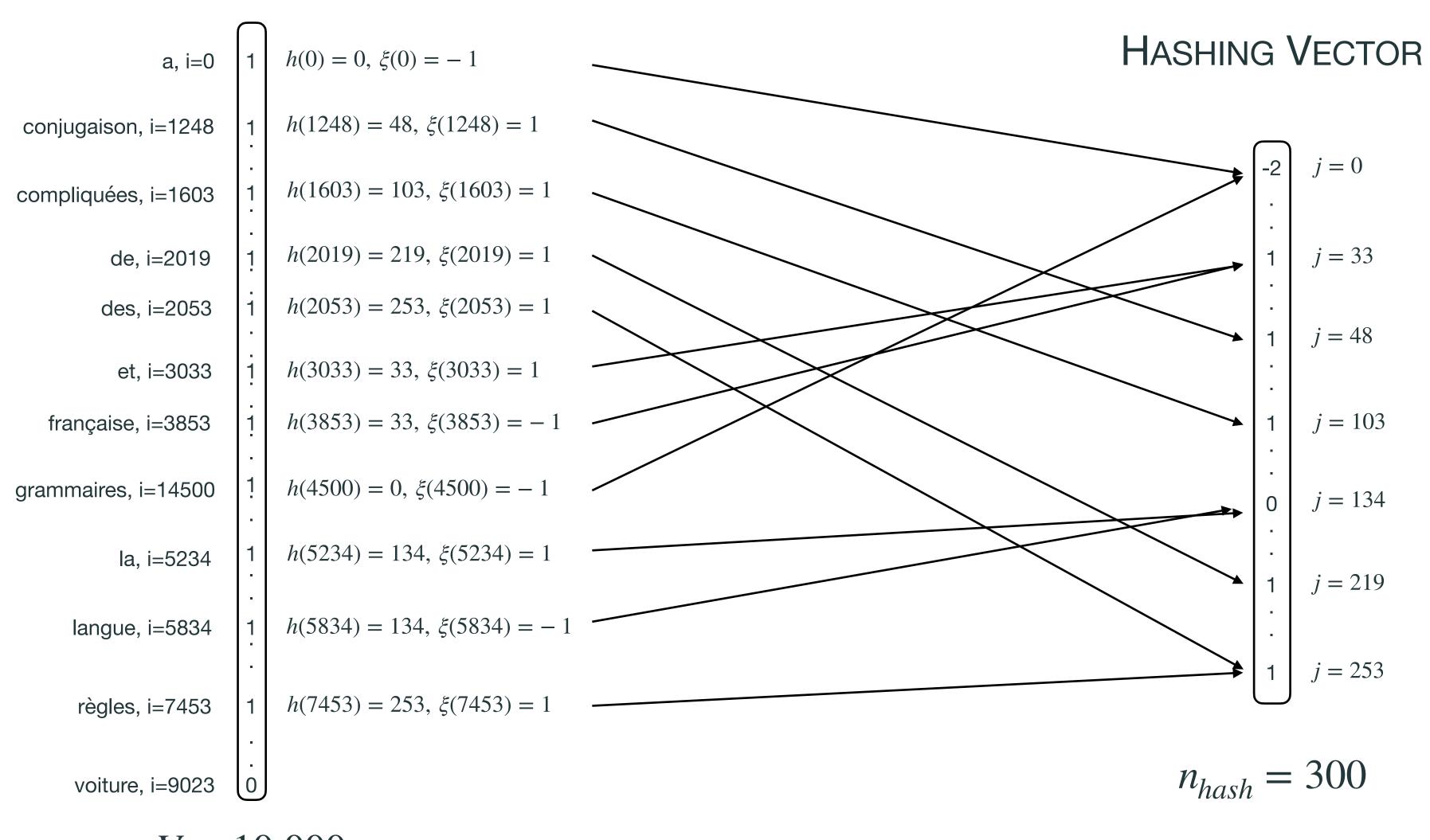
And

$$\xi \colon \mathbb{N} \to \{1, ..., -1\}$$

$$i \mapsto j = \xi(i)$$

HASHING [WEINBERGER AND AL, 2009]

BINARY VECTORISER



APPLICATION OF VECTORISATION FOR LEARNING

- Hashing and then TF-IDF are applied on training dataset.
- Same hashing function are used on test dataset.
- TF value between a word t and a document d are recomputed for the test dataset.
- IDF terms computed during training are re-used.

N-GRAMS

PROBLEMS

Some words does not have the same sense according to the context where it used.

Short de bain ≠ short ≠ bain

SOLUTION

We consider not only the word (*unigram*) but also succession of two (*bigram*) or more words (*n-gram*).

- Solve language ambiguity.
- Explosion of vectors size. Example:
 - For 21.543 lines of categorise "TELEPHONIE GPS"
 - •8.384 unigrams, 50.012 bigram, 90.854 trigram...

TP

- Clean Cdiscount text's dataset.
- Vectorize and hash text dataset using scikit-learn library.
- Apply product classification on vectorised data.