Atelier 5 : Topic Mining

L'objectif de cet atelier est de decouvrire le "Topic Mining" à travers un dataset de news. Le dataset comprend 18846 posts appartenant à 20 topics differents et qui sont reparties en deux groupes: un dataset d'apprentissage et un dataset de test.

1. Praitraitements / NLP

1.1 Recuperration du corpus

```python
from sklearn.datasets import fetch_20newsgroups
#fetch return a brunch that is a dictionary-like object, with the following attributes.
dataset = fetch_20newsgroups(subset='train')
data=dataset.data
targets=dataset.target
print(dataset.target_names)
print(data[3],targets[0])
```

```
['alt.atheism', 'comp.graphics', 'comp.os.ms-windows.misc',
'comp.sys.ibm.pc.hardware', 'comp.sys.mac.hardware', 'comp.windows.x',
'misc.forsale', 'rec.autos', 'rec.motorcycles', 'rec.sport.baseball',
'rec.sport.hockey', 'sci.crypt', 'sci.electronics', 'sci.med',
'sci.space', 'soc.religion.christian', 'talk.politics.guns',
'talk.politics.mideast', 'talk.politics.misc', 'talk.religion.misc']
From: jgreen@amber (Joe Green)
Subject: Re: Weitek P9000 ?
Organization: Harris Computer Systems Division
Lines: 14
Distribution: world
NNTP-Posting-Host: amber.ssd.csd.harris.com
X-Newsreader: TIN [version 1.1 PL9]

Robert J.C. Kyanko (rob@rjck.UUCP) wrote:
> abraxis@iastate.edu writes in article
<abraxis.734340159@class1.iastate.edu>:
> > Anyone know about the Weitek P9000 graphics chip?
> As far as the low-level stuff goes, it looks pretty nice.  It's got
this
> quadrilateral fill command that requires just the four points.

Do you have Weitek's address/phone number?  I'd like to get some
information
about this chip.

--
```

```
Joe Green                    Harris Corporation
jgreen@csd.harris.com             Computer Systems Division
"The only thing that really scares me is a person with no sense of
humor."
                                     -- Jonathan Winters
 7
```

1.2 Cleaning

Le corpus comporte des posts qui necessitent un cleaning afin de ne garder que les donnees qui vont nous servir dans l'opération du topic mining.

- supprimer les emails
- supprimer les adresses des sites web
- supprimer les nombres et les caractères spéciaux
- supprimer les stopwords(on la reporte vers l'étape de vectorisation)
- supprimer les terms non sigificatifs (non anglais)

Utiliser la librairie RE pour la manipulation des expressions regulière

```
'''
.           Wildcard, matches any character
^abc      Matches some pattern abc at the start of a string
abc$      Matches some pattern abc at the end of a string
[abc]     Matches one of a set of characters
[A-Z0-9]   Matches one of a range of characters
ed|ing|s   Matches one of the specified strings (disjunction)
*            Zero or more of previous item, e.g. a*, [a-z]* (also
known as Kleene Closure)
+            One or more of previous item, e.g. a+, [a-z]+
?            Zero or one of the previous item (i.e. optional), e.g.
a?, [a-z]?
{n}          Exactly n repeats where n is a non-negative integer
{n,}      At least n repeats
{,n}      No more than n repeats
{m,n}     At least m and no more than n repeats
a(b|c)+        Parentheses that indicate the scope of the operators
'''


'''
\number
Correspond au contenu du groupe du même nombre. Les groupes sont
numérotés à partir de 1. Par exemple, (.+) \1 correspond à 'the the'
ou '55 55', mais pas à 'thethe' (notez l’espace après le groupe).
Cette séquence spéciale ne peut être utilisée que pour faire référence
aux 99 premiers groupes. Si le premier chiffre de number est 0, ou si
number est un nombre octal de 3 chiffres, il ne sera pas interprété
comme une référence à un groupe, mais comme le caractère à la valeur
```

```
octale number. À l’intérieur des '[' et ']' d’une classe de
caractères, tous les échappements numériques sont traités comme des
caractères.

\A
Correspond uniquement au début d’une chaîne de caractères.

\b
Correspond à la chaîne vide, mais uniquement au début ou à la fin d’un
mot. Un mot est défini comme une séquence de « caractères de mots ».
Notez que formellement, \b est défini comme la liaison entre \w et \W
(et inversement), ou entre \w et le début/fin d’un mot. Cela signifie
que r'\bfoo\b' validera 'foo', 'foo.', '(foo)' ou 'bar foo baz' mais
pas 'foobar' ou 'foo3'.

Les caractères alphanumériques Unicode sont utilisés par défaut dans
les motifs Unicode, mais cela peut être changé en utilisant l’option
ASCII. Les délimitations de mots sont déterminées par la locale si
l’option LOCALE est utilisée. À l’intérieur d’un intervalle de
caractères, \b représente le caractère backspace, par compatibilité
avec les chaînes littérales Python.

\B
Correspond à la chaîne vide, mais uniquement quand elle n’est pas au
début ou à la fin d’un mot. Cela signifie que r'py\B' valide 'python',
'py3' ou 'py2', mais pas 'py', 'py.' ou 'py!'. \B est simplement
l’opposé de \b, donc les caractères de mots dans les motifs Unicode
sont les alphanumériques et tirets bas Unicode, bien que cela puisse
être changé avec l’option ASCII. Les délimitations de mots sont
déterminées par la locale si l’option LOCALE est utilisée.

\d
Pour les motifs Unicode (str) :
Valide n’importe quel chiffre décimal Unicode (soit tout caractère
Unicode de catégorie [Nd]). Cela inclue [0-9], mais aussi bien
d’autres caractères de chiffres. Si l’option ASCII est utilisée, seuls
les caractères de la classe [0-9] correspondront (mais l’option
affectant l’expression rationnelle entière, il peut être préférable
dans ce genre de cas d’utiliser un [0-9] explicite).

Pour les motifs 8-bit (bytes) :
Valide n’importe quel chiffre décimal ; équivalent à [0-9].

\D
Valide tout caractère qui n’est pas un chiffre décimal. C’est l’opposé
de \d. Si l’option ASCII est utilisée, cela devient équivalent à [^0-
9] (mais l’option affectant l’expression rationnelle entière, il peut
être préférable dans ce genre de cas d’utiliser explicitement [^0-9]).

\s
```

```
Pour les motifs Unicode (str) :
Valide les caractères d'espacement Unicode (qui incluent [ \t\n\r\f\v]
et bien d'autres, comme les espaces insécables requises par les règles
typographiques de beaucoup de langues). Si l'option ASCII est
utilisée, seuls les caractères de la classe [ \t\n\r\f\v] sont validés
(mais l'option affectant l'expression rationnelle entière, il peut
être préférable dans ce genre de cas d'utiliser un [ \t\n\r\f\v]
explicite).

Pour les motifs 8-bit (bytes) :
Valide les caractères considérés comme des espacements dans la table
ASCII ; équivalent à [ \t\n\r\f\v].

\S
Valide tout caractère qui n'est pas un caractère d'espacement. c'est
l'opposé de \s. Si l'option ASCII est utilisée, cela devient
équivalent à [^ \t\n\r\f\v] (mais l'option affectant l'expression
rationnelle entière, il peut être préférable dans ce genre de cas
d'utiliser un [^ \t\n\r\f\v] explicite).

\w
Pour les motifs Unicode (str) :
Valide les caractères Unicode de mot ; cela inclut la plupart des
caractères qui peuvent être compris dans un mot d'une quelconque
langue, aussi bien que les nombres et les tirets bas. Si l'option
ASCII est utilisée, seuls les caractères de la classe [a-zA-Z0-9_]
sont validés (mais l'option affectant l'expression rationnelle
entière, il peut être préférable dans ce genre de cas d'utiliser un
[a-zA-Z0-9_] explicite).

Pour les motifs 8-bit (bytes) :
Valide les caractères alphanumériques de la table ASCII ; équivalent à
[a-zA-Z0-9_]. Si l'option LOCALE est utilisée, les caractères
considérés alphanumériques dans la locale et le tiret bas seront
acceptés.

\W
Valide tout caractère qui n'est pas un caractère de mot. C'est
l'opposé de \w. Si l'option ASCII est utilisée, cela devient
équivalent à [^a-zA-Z0-9_] (mais l'option affectant l'expression
rationnelle entière, il peut être préférable dans ce genre de cas
d'utiliser un [^a-zA-Z0-9_] explicite). Si l'option LOCALE est
utilisée, les caractères considérés alphanumériques dans la locale
courrante, et le tiret bas, seront acceptés.

\Z
Correspond uniquement à la fin d'une chaîne de caractères
'''

import re
```

```
def cleaninng(doc):
    return re.sub("\S+@\S+|(www\S+)|[0-9]+|[@_!#$%^&*()<>?/\|}
{~:]*","", doc)


data= [cleaninng(doc) for doc in data]

import nltk
nltk.download('words')

'''Supprimer les terms non anglais'''
words = set(nltk.corpus.words.words())
def English(doc):
    return " ".join(w for w in nltk.wordpunct_tokenize(doc) if
w.lower() in words)

data= [English(doc) for doc in data]
print(data[0],targets[0])
```

```
[nltk_data] Downloading package words to
[nltk_data]     C:\Users\dscon\AppData\Roaming\nltk_data...
[nltk_data]   Package words is already up-to-date!

From where s my thing Subject WHAT car is this Posting Host
Organization University of College Park I was wondering if anyone out
there could enlighten me on this car I saw the other day It was a door
sports car to be from the late s early s It was a The were really
small In addition the front bumper was separate from the rest of the
body This is all I know If anyone can a model name engine specs of
production where this car is made history or whatever you have on this
funky looking car please e mail Thanks brought to you by your
neighborhood 7
```

1.2 Lemmatisation

```
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import word_tokenize
from nltk.corpus import stopwords
from nltk.corpus import words

lemmatizer=WordNetLemmatizer()

def lemmatization(doc):
    '''lemmatisation du document doc'''
    return " ".join(lemmatizer.lemmatize(w) for w in
word_tokenize(doc))


corpus_lemetized=[lemmatization(doc) for doc in data]
print(corpus_lemetized[0])
```

```
From where s my thing Subject WHAT car is this Posting Host
Organization University of College Park I wa wondering if anyone out
there could enlighten me on this car I saw the other day It wa a door
sport car to be from the late s early s It wa a The were really small
In addition the front bumper wa separate from the rest of the body
This is all I know If anyone can a model name engine spec of
production where this car is made history or whatever you have on this
funky looking car please e mail Thanks brought to you by your
neighborhood
```

2. Approche Mono-Terme

Récupérer la représentation vectorielle des differents documents avec le TF-IDF

```
corpus_lemetized[:10]
```

```
['From where s my thing Subject WHAT car is this Posting Host
Organization University of College Park I wa wondering if anyone out
there could enlighten me on this car I saw the other day It wa a door
sport car to be from the late s early s It wa a The were really small
In addition the front bumper wa separate from the rest of the body
This is all I know If anyone can a model name engine spec of
production where this car is made history or whatever you have on this
funky looking car please e mail Thanks brought to you by your
neighborhood',
 'From Guy Subject SI Clock Poll Final Call Summary Final call for SI
clock SI acceleration clock upgrade Article I D Organization
University of Posting Host u A fair number of brave who their SI clock
oscillator have their for this poll Please send a brief message your
with the procedure Top speed rated speed add on and heat hour of usage
per day floppy disk functionality with and m are especially I will be
in the next two day so please add to the network knowledge base if you
have done the clock upgrade and haven t this poll Thanks Guy',
 'From E Subject Organization University Engineering Computer Network
Distribution well my mac plus finally gave up the ghost this weekend
after starting life a a k way back in i m in the market for a new
machine a bit sooner than i intended to be i m looking into up a or
maybe and have a bunch of that hopefully somebody can answer doe
anybody know any dirt on when the next round of are i d the c wa
supposed to make an this summer but haven t on it and since i don t
have access to i wa wondering if anybody out there had more anybody
about price to the line like the the duo s just went through recently
what s the impression of the display on the i could probably swing a
if i got the disk rather than the but i don t really have a feel for
how much better the display is yea it great in the store but is that
all wow or is it really that good could i solicit some of people who
use the and day to day on if it worth taking the disk size and money
```

```
hit to get the active display i realize this is a real subjective
question but i only around with the in a computer store and figured
the of somebody who actually the machine daily might prove helpful how
well doe perform thanks a bunch in advance for any if you could i post
a summary news reading time is at a premium with just around the
corner Electrical Engineering are more dangerous of truth than F W',
 'From Joe Green Subject Re P Organization Computer Division
Distribution world Posting Host amber X Newsreader TIN version J C
wrote in article Anyone know about the P graphic chip As far a the low
level stuff go it pretty nice It s got this quadrilateral fill command
that just the four Do you have s number I d like to get some
information about this chip Joe Green Corporation Computer Division
The only thing that really me is a person with no sense of humor',
 'From Subject Re Shuttle Launch Question Organization Astrophysical
Observatory MA Distribution From article by A Baker In article Pack
Rat Clear caution warning memory Verify no unexpected I am wondering
what an error might be Sorry if this is a really dumb question but
Parity in memory or previously known that were Yes that is an error
but we already knew about it I d be curious a to what the real meaning
of the quote is My understanding is that the are basically known in
the warning system are checked that don t have the right in yet
because they t set till after launch and suchlike Rather than fix the
code and possibly introduce new they just tell the crew if you see a
warning no before ignore it',
 'From Subject Re the Second Amendment Organization In article C D In
article In article C D In article The massive destructive power of
many modern the cost of an accidental or usage of these to great The
of mass destruction need to be in the control of the government only
Individual access would result in the needle of million This the right
of the people to keep and bear many modern non Thanks for where you re
coming from Needless to say I disagree on every count You believe that
should have the right to own of mass destruction I find it hard to
believe that you would support a neighbor s right to keep nuclear
biological and nerve gas on property If we can not even agree on
keeping of mass destruction out of the of can there be any hope for u
I don t sign any blank Of course The term must be rigidly defined in
any bill When of mass destruction he and When of mass destruction she
Street Sweeper and semi automatic I doubt she this term for that You
are a quote allegedly from her can you back it up When of mass
destruction and then immediately it with The US of people each year by
this number can easily be reduced by reasonable on them what doe mean
by the term I read the article a first an argument about of mass
destruction a commonly understood and then switching to other The
first point evidently wa to show that not all should be and then the
later analysis wa given this understanding to consider another class
If you believe that I speak for my company OR write today for my
special Packet',
 'From manning Subject Brain Tumor Treatment thanks Reply To
Organization University of There were a few people who to my request
```

```
for on treatment for through whom I t thank directly because of mail
bouncing and So I thought I d publicly thank everyone Thanks I m sure
glad I accidentally hit instead of when I wa trying to delete a file
last News What s this',
 'From Subject Re IDE Organization New State University Las Cruces
Distribution world Posting Host In article In Magazine Although is
twice a a faster than IDE and support up to it acceptance long been by
and installation I love it when magazine make stupid like that re
performance Where do they get those I list the actual performance
which should convince anyone that such a statement is absurd I from
from IDE from is always although there are some non standard ALL this
is that YOU don t know much about with a chip range is indeed and that
is ALL you have right about With a controller chip with burst bit Note
the INCREASE in SPEED the Mac Quadra this version of so it DOES exist
Some use this set up too mode with burst or fast mode with burst AND
fast with burst By your OWN data the Although is twice a fast a is
correct With a controller chip can reach which is indeed faster than
IDE of is ALL these have been posted to this in my Mac sheet available
by on aim in the a mac compare version It should be but may still be
there Part of this problem is both Mac and are about what is which
Though it is WELL that the Quadra a chip an Apple salesperson said it
a fast chip Not at a burst it doe not is maximum synchronous and
Quadra which is It that Mac and see interface and think when it maybe
a interface driven in the machine by a controller chip in bit mode
Which is MUCH FASTER then true can go Don t slam an article because
you don t understand what is going on One reference for the Quadra s
controller chip is Digital Review v n p',
 'From Subject WIn ICON HELP PLEASE Organization University of
Northern I have win and several and s but I can t figure out how to
change the wallpaper or use the Any help would be Please E mail me',
 'From Subject Re Sigma Double up Article I D B Organization
University of at A I am looking for any information about the Sigma
double up board All I can figure out is that it is a hardware
compression board that work with but I am not sure about this Also how
much would one cost I had the board for over a year and it doe work
with but not with due to a problem with the of the board s compression
technology I m writing this from memory I lost the reference Please
correct me if I m wrong the board I had with file being lost but it s
hard to say whether it s the board s fault or something else however
if I decompress the file and recompress it without the board the icon
usually Because of the above problem the expansion utility Expand will
not decompress a board compressed file unless you have the board Since
it own product now it unlikely that the in related to the board will
be fixed Which is sad and me very reluctant to buy s product since
they re being so But hey that s competition Office U of Phone']

from sklearn.feature_extraction.text import TfidfVectorizer
import pandas as pd

vectorizer = TfidfVectorizer(stop_words = 'english')
```

```
vect = vectorizer.fit_transform(corpus_lemetized)
pd.DataFrame(vect.toarray(),
columns=vectorizer.get_feature_names_out())

        aa  aal  aba  abacus  abandon  abandoned  abandonment
abate  \
0      0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

1      0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

2      0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

3      0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

4      0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

...    ...  ...  ...     ...      ...        ...          ...    ...

11309  0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

11310  0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

11311  0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

11312  0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

11313  0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0


       abatement  abbey  ...  zone  zoning  zoo  zooid  zoological
zoology  \
0            0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
1            0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
2            0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
3            0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
4            0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
...          ...    ...  ...   ...     ...  ...    ...         ...
...
11309        0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
11310        0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
11311        0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
11312        0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
```

```
11313        0.0    0.0  ...   0.0     0.0  0.0    0.0          0.0
0.0

       zoom  zorro  zowie  zucchini
0       0.0    0.0    0.0       0.0
1       0.0    0.0    0.0       0.0
2       0.0    0.0    0.0       0.0
3       0.0    0.0    0.0       0.0
4       0.0    0.0    0.0       0.0
...     ...    ...    ...       ...
11309   0.0    0.0    0.0       0.0
11310   0.0    0.0    0.0       0.0
11311   0.0    0.0    0.0       0.0
11312   0.0    0.0    0.0       0.0
11313   0.0    0.0    0.0       0.0

[11314 rows x 21174 columns]
```

Réaliser une fonction de scoring qui permettra de déterminer les mots les plus pertinents pour être des topics.

```
import numpy
def scoring(k):
    ''''Proposer un traitement qui retourne la liste  des k termes les plus pertinents'''

    vect=vect.toarray()
    feature_names=vectorizer.get_feature_names()
    scores=[]
    for i in range(0, len(vect[0])):
        s=[vect[j][i] for j in range(len(vect))]
        scores.append(numpy.mean(s))
    topics=[]
    for i in range(k):
        topics.append(feature_names[scores.index(max(scores))])
        feature_names.pop(scores.index(max(scores)))
        scores.pop(scores.index(max(scores)))

    return topics, feature_names,scores
```

Modifier le code precedent pour identifier les topics similaires (selon un seuil predeterminé) et ne garder que le plus pertinents. chaque terme supprimé doit etre remplacé par le terme suivant dans la liste des scores.

- Utiliser l'approche semantique lexicale
- Utiliser l'approche semantiqe statistique: le wordembedding

```
def scoring_v2(k, seuil=0.7):
    topics, feature_names,scores= scoring(k)
```

```
    print(f"Topics {topics}, feature_names {feature_names}, scores 
{scores}")
    for i in range(0,len(topics)-1):
        for j in range(i+1, len(topics)):
            if sim(topics[i],topics[i])>=seuil:
                topics[j]=feature_names.pop(scores.index(max(scores)))
                scores.pop(scores.index(max(scores)))
    return topics

def sim(t1,t2):
    "a completer"
    t1_vector=vect[:,vectorizer.get_feature_names_out().index(t1)]
    t2_vector=vect[:,vectorizer.get_feature_names_out().index(t2)]
    return 
numpy.dot(t1_vector,t2_vector)/(numpy.linalg.norm(t1_vector)*numpy.lin
alg.norm(t2_vector))
```

Calculer la distribution des topics par documents.

```
# computes topics distribution for each document
def topics_distribution(corpus, topics):
    vect=vectorizer.transform(corpus).toarray()
    feature_names=vectorizer.get_feature_names_out()
    scores=[]
    for i in range(0, len(vect[0])):
        s=[vect[j][i] for j in range(len(vect))]
        scores.append(numpy.mean(s))
    topics_distribution=[]
    for i in range(len(corpus)):
        topics_distribution.append([numpy.mean([vect[i]
[feature_names.index(t)] for t in topics]) for t in topics])
    return topics_distribution
```

Essayer d'ameliorer les resultats obtenus en utilisant par exemple un vocabulaire preetabli ou en ne considerant que les parties significatives du document(Subject, Summary, keywords...)

2. LSA

Vectorisation

```
from sklearn.feature_extraction.text import TfidfVectorizer
data_lemetized = corpus_lemetized
vectorizer = TfidfVectorizer(stop_words = 'english')
vect = vectorizer.fit_transform(data_lemetized)
```

```
import pandas as pd
pd.DataFrame(vect.toarray(),
columns=vectorizer.get_feature_names_out())
```

```
        aa   aal  aba  abacus  abandon  abandoned  abandonment
abate  \
0      0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

1      0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

2      0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

3      0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

4      0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

...    ...  ...  ...     ...      ...        ...          ...    ...

11309  0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

11310  0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

11311  0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

11312  0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0

11313  0.0  0.0  0.0     0.0      0.0        0.0          0.0    0.0


       abatement  abbey  ...  zone  zoning  zoo  zooid  zoological
zoology  \
0            0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
1            0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
2            0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
3            0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
4            0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
...          ...    ...  ...   ...     ...  ...    ...         ...
...
11309        0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
11310        0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
11311        0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
11312        0.0    0.0  ...   0.0     0.0  0.0    0.0         0.0
0.0
```

```
11313         0.0    0.0  ...   0.0     0.0  0.0    0.0          0.0
0.0

       zoom  zorro  zowie  zucchini
0       0.0    0.0    0.0       0.0
1       0.0    0.0    0.0       0.0
2       0.0    0.0    0.0       0.0
3       0.0    0.0    0.0       0.0
4       0.0    0.0    0.0       0.0
...     ...    ...    ...       ...
11309   0.0    0.0    0.0       0.0
11310   0.0    0.0    0.0       0.0
11311   0.0    0.0    0.0       0.0
11312   0.0    0.0    0.0       0.0
11313   0.0    0.0    0.0       0.0

[11314 rows x 21174 columns]
```

Decomposition SVD de notre corpus selon le vocabulaire

```python
from sklearn.decomposition import TruncatedSVD
k=20
lsa= TruncatedSVD(n_components=k)
U = lsa.fit_transform(vect)
D= lsa.singular_values_
V_T = lsa.components_.T
```

Visualisation

```python
doc_topic_matrix=pd.DataFrame(data=U, index = [f'Doc_{r}' for r in
range(0,U.shape[0])], columns = [f'Topic_{r}' for r in
range(0,V_T.shape[1])])
doc_topic_matrix
```

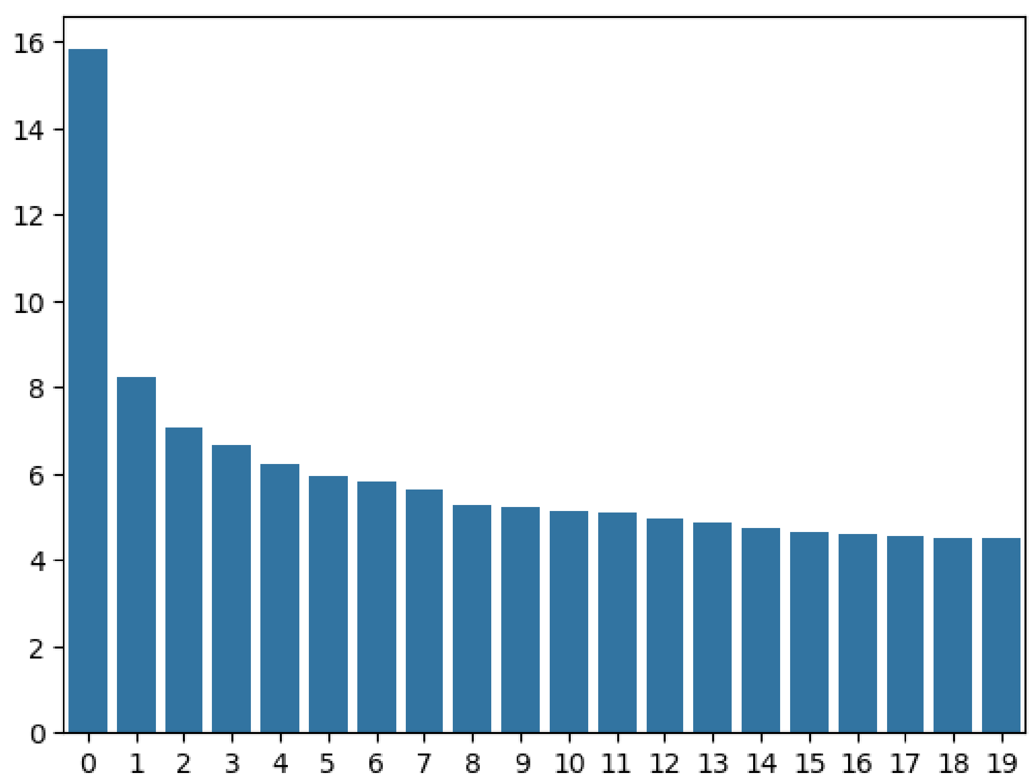
```
             Topic_0   Topic_1   Topic_2   Topic_3   Topic_4   Topic_5
\
Doc_0       0.201049  0.018957 -0.100200 -0.083000  0.019760 -0.048634

Doc_1       0.094243 -0.054455 -0.019245 -0.003359  0.024625 -0.030699

Doc_2       0.282567 -0.043107 -0.025821  0.026318  0.030342  0.031593

Doc_3       0.215606 -0.085882  0.073654 -0.053396 -0.050755 -0.047127

Doc_4       0.132909 -0.006618 -0.000254  0.020322 -0.005049  0.033091

...              ...       ...       ...       ...       ...       ...

Doc_11309   0.109639  0.027184 -0.002600 -0.004240  0.002099  0.005672
```

```
Doc_11310  0.176286 -0.173972 -0.051537  0.063340  0.127914 -0.063321
Doc_11311  0.086185 -0.013880  0.013670 -0.009567  0.016779  0.002390
Doc_11312  0.109684 -0.017480  0.008716 -0.001000 -0.048531  0.001305
Doc_11313  0.099094 -0.055844  0.021216 -0.033907 -0.036930 -0.040615

            Topic_6   Topic_7   Topic_8   Topic_9  Topic_10  Topic_11
\
Doc_0     -0.142208  0.054754 -0.105393  0.282671  0.173009 -0.069159
Doc_1      0.001780 -0.015681  0.016047  0.010935  0.017994 -0.029507
Doc_2     -0.009796  0.004135 -0.015778  0.024754  0.029986 -0.030362
Doc_3      0.036138  0.018168 -0.008285  0.006247  0.089918 -0.037392
Doc_4     -0.023172 -0.018143  0.028644  0.009638 -0.017265 -0.040985
...             ...       ...       ...       ...       ...       ...
Doc_11309 -0.030809  0.005625 -0.030100 -0.029230 -0.013865 -0.012708
Doc_11310 -0.000056  0.007993  0.003894  0.047368 -0.038447  0.089894
Doc_11311  0.005412  0.004298  0.019261  0.041875  0.054796  0.016095
Doc_11312 -0.036650 -0.020940  0.081933  0.013913 -0.067112 -0.052768
Doc_11313 -0.014027  0.004400 -0.019014  0.015463  0.034589 -0.013113

           Topic_12  Topic_13  Topic_14  Topic_15  Topic_16  Topic_17
\
Doc_0      0.116471 -0.057345 -0.134113 -0.015518 -0.134130 -0.047927
Doc_1     -0.027169 -0.003665  0.007166 -0.008071 -0.004519  0.006321
Doc_2     -0.025610  0.113475 -0.013521  0.003046 -0.023865  0.030588
Doc_3     -0.061607  0.012818  0.001445 -0.024082  0.131321  0.059810
Doc_4     -0.053333 -0.018445  0.031038 -0.020700  0.008082  0.018968
...             ...       ...       ...       ...       ...       ...
Doc_11309 -0.010025  0.019430 -0.006756  0.005582  0.011135  0.024112
Doc_11310 -0.131442  0.226776 -0.003724 -0.005212 -0.039195 -0.072129
```

```
Doc_11311  0.006456  0.011938  0.005243  0.020700  0.065867  0.002545

Doc_11312 -0.064337 -0.019536 -0.002127  0.006118 -0.012551 -0.000999

Doc_11313 -0.009703 -0.017008  0.012158 -0.004137 -0.041083 -0.036359


           Topic_18  Topic_19
Doc_0     -0.029631  0.025309
Doc_1     -0.048228  0.044349
Doc_2     -0.024894 -0.006588
Doc_3      0.068339  0.041099
Doc_4     -0.031523  0.018181
...             ...       ...
Doc_11309  0.007994  0.000467
Doc_11310  0.071824  0.088662
Doc_11311  0.020886 -0.011235
Doc_11312  0.037439 -0.025444
Doc_11313 -0.028825 -0.013774

[11314 rows x 20 columns]
```

```python
import seaborn as sns
sns.barplot(x=list(range(len(D))), y = D)
```

```
<Axes: >
```



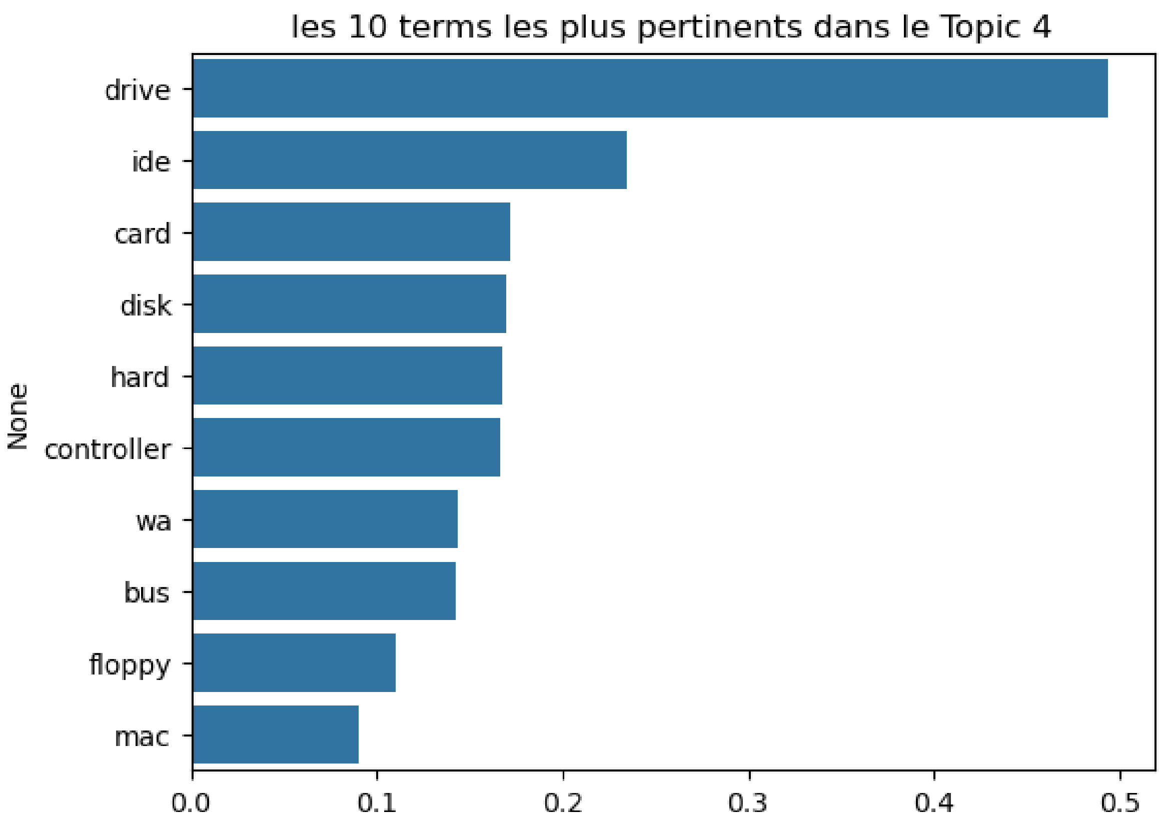
```python
term_topic_matrix=pd.DataFrame(data=V_T, index =
vectorizer.get_feature_names_out(), columns = [f'Topic_{r}' for r in
range(0,V_T.shape[1])])
term_topic_matrix
```

```
               Topic_0       Topic_1       Topic_2       Topic_3  \
aa        4.282446e-03 -2.087794e-03 -2.349240e-03 -1.101943e-03
aal       4.908270e-09  6.778901e-09  1.037278e-08 -5.778333e-09
aba       1.510421e-05 -2.380714e-05 -2.573328e-05 -1.927864e-05
abacus    2.878948e-05 -7.202851e-05 -1.890233e-05  5.254051e-06
abandon   1.293472e-03  1.314995e-03  3.199440e-04  1.230498e-03
...                ...           ...           ...           ...
zoology   5.360945e-03  2.360869e-03  3.533069e-03 -8.639385e-04
zoom      1.969979e-03 -3.445253e-03 -1.238400e-03  5.650986e-04
zorro     3.630471e-04 -9.069579e-04 -1.561199e-04  5.891716e-04
zowie     3.321747e-05  1.569618e-05 -1.261575e-05 -4.893662e-05
zucchini  1.117876e-04  1.488255e-05 -2.374040e-05 -5.478078e-06

               Topic_4       Topic_5       Topic_6       Topic_7  \
aa       -2.716246e-04  2.891420e-03  3.402090e-03 -1.988603e-03
aal       3.048822e-08  6.762998e-08 -8.118216e-08  2.506560e-09
aba      -7.926892e-06 -4.096039e-05 -1.142726e-05 -1.010891e-05
abacus   -6.512409e-05 -7.399320e-05 -4.630261e-05 -3.533896e-05
abandon  -3.118637e-04  1.035573e-03 -9.068182e-04 -2.304078e-04
...                ...           ...           ...           ...
zoology   8.089601e-03  1.109797e-02 -1.293499e-02 -4.796266e-03
zoom     -1.217531e-03 -2.788210e-03 -2.319263e-03  1.830725e-03
zorro     2.935354e-03 -7.308243e-04  4.780198e-04 -5.068625e-04
zowie     2.874874e-05  3.594656e-05 -1.238253e-04 -7.658322e-06
zucchini  2.295928e-04  2.039013e-04 -1.406350e-04 -6.846779e-06

               Topic_8       Topic_9      Topic_10      Topic_11  \
aa       -5.537219e-03  5.002595e-03  3.895707e-03  5.840312e-03
aal       2.663134e-08 -2.082753e-07 -1.243470e-08  1.921600e-07
aba       1.708699e-05 -6.704603e-06 -2.287704e-06  2.435809e-05
abacus   -4.181054e-05  5.659950e-05  1.796245e-04  1.393688e-04
abandon   1.717509e-04 -2.521453e-03  7.514328e-04  1.074987e-03
...                ...           ...           ...           ...
zoology   1.185335e-02  2.099578e-02  2.820002e-02 -3.090986e-02
zoom     -2.626696e-03  2.126852e-03  4.818986e-03  3.388893e-03
zorro     1.137683e-03 -1.732676e-03 -8.484088e-04 -1.110939e-03
zowie    -1.445378e-04  1.669743e-04  8.593628e-05 -1.944951e-04
zucchini -2.421267e-04  1.596834e-04 -1.891177e-05 -8.905155e-05

              Topic_12      Topic_13      Topic_14      Topic_15  \
aa        2.856384e-03  2.539186e-03 -7.212120e-04  5.761525e-03
aal      -3.919984e-08 -4.046733e-08 -3.071457e-07 -4.188966e-08
aba      -2.752594e-05  3.395388e-05 -9.249110e-07  1.119426e-05
abacus    1.325906e-04  8.237088e-05  1.273765e-05  5.940998e-05
abandon   1.701924e-03 -1.742212e-04  2.096712e-03 -3.144573e-04
```

```
...                  ...           ...           ...           ...
zoology  -1.276788e-02 -2.113484e-02  5.325709e-03  4.620997e-03
zoom      2.381565e-03  4.769016e-03 -8.877203e-05 -3.808612e-03
zorro     4.235523e-05 -3.744263e-03 -1.291009e-03  4.875110e-04
zowie    -3.131272e-05 -1.590205e-04  2.355918e-05  2.119893e-05
zucchini -1.878518e-04  2.131490e-04  1.141997e-04  2.387355e-04

              Topic_16      Topic_17      Topic_18      Topic_19
aa       -5.792518e-03  1.303627e-03 -4.242090e-03  1.720669e-03
aal       2.146793e-07 -1.571782e-07 -1.663685e-07 -2.538775e-07
aba      -1.146936e-05 -7.830925e-05 -7.129283e-06 -3.258532e-05
abacus   -6.238603e-05  9.281606e-05  2.038020e-06  1.833060e-04
abandon   1.431644e-04  3.807202e-04 -8.912843e-04 -1.315051e-03
...                ...           ...           ...           ...
zoology   6.294611e-03 -9.814336e-03  9.677835e-03  2.411162e-03
zoom     -3.649723e-03  3.900331e-03  6.377640e-04 -3.015394e-03
zorro    -4.660029e-03  2.462243e-03  3.676236e-03 -1.757733e-03
zowie     7.096774e-05 -3.354733e-05 -1.209071e-05  1.264046e-04
zucchini  2.256169e-04 -2.118050e-04 -3.853502e-05  2.011310e-04

[21174 rows x 20 columns]
```

```python
from matplotlib import pyplot as plt
import seaborn as sns

data = term_topic_matrix[f'Topic_4']
data = data.sort_values(ascending=False)
top_10 = data[:10]
title='les 10 terms les plus pertinents dans le Topic 4'
plt.title(title)
sns.barplot(x= top_10.values, y=top_10.index)
```

```
<Axes: title={'center': 'les 10 terms les plus pertinents dans le
Topic 4'}, ylabel='None'>
```



3. LDA

Vectorisation

```
from sklearn.feature_extraction.text import CountVectorizer

#Bag of words
vectorizer = CountVectorizer(stop_words = 'english')
vect = vectorizer.fit_transform(corpus_lemetized)
```

Modèle LDA

```
from sklearn.decomposition import LatentDirichletAllocation


alpha=1/20 # valeur par defaut
eta=1/20 # valeur par defaut
lda =
LatentDirichletAllocation(n_components=20,doc_topic_prior=alpha,topic_
word_prior=eta)
theta=lda.fit_transform(vect) #  distribution topics/document
beta=lda.components_  #  distribution mots/topics
```

Evaluation

```
# Log Likelyhood: Higher the better
print("Likelihood: ", lda.score(vect))
# Perplexity: Lower the better.
print("Perplexité: ", lda.perplexity(vect))
# visualisation des parametres du modèle
print(lda.get_params())
```

```
Likelihood:  -7910792.748932846
Perplexité:  1620.3730679387234
{'batch_size': 128, 'doc_topic_prior': 0.05, 'evaluate_every': -1,
'learning_decay': 0.7, 'learning_method': 'batch', 'learning_offset':
10.0, 'max_doc_update_iter': 100, 'max_iter': 10, 'mean_change_tol':
0.001, 'n_components': 20, 'n_jobs': None, 'perp_tol': 0.1,
'random_state': None, 'topic_word_prior': 0.05, 'total_samples':
1000000.0, 'verbose': 0}
```

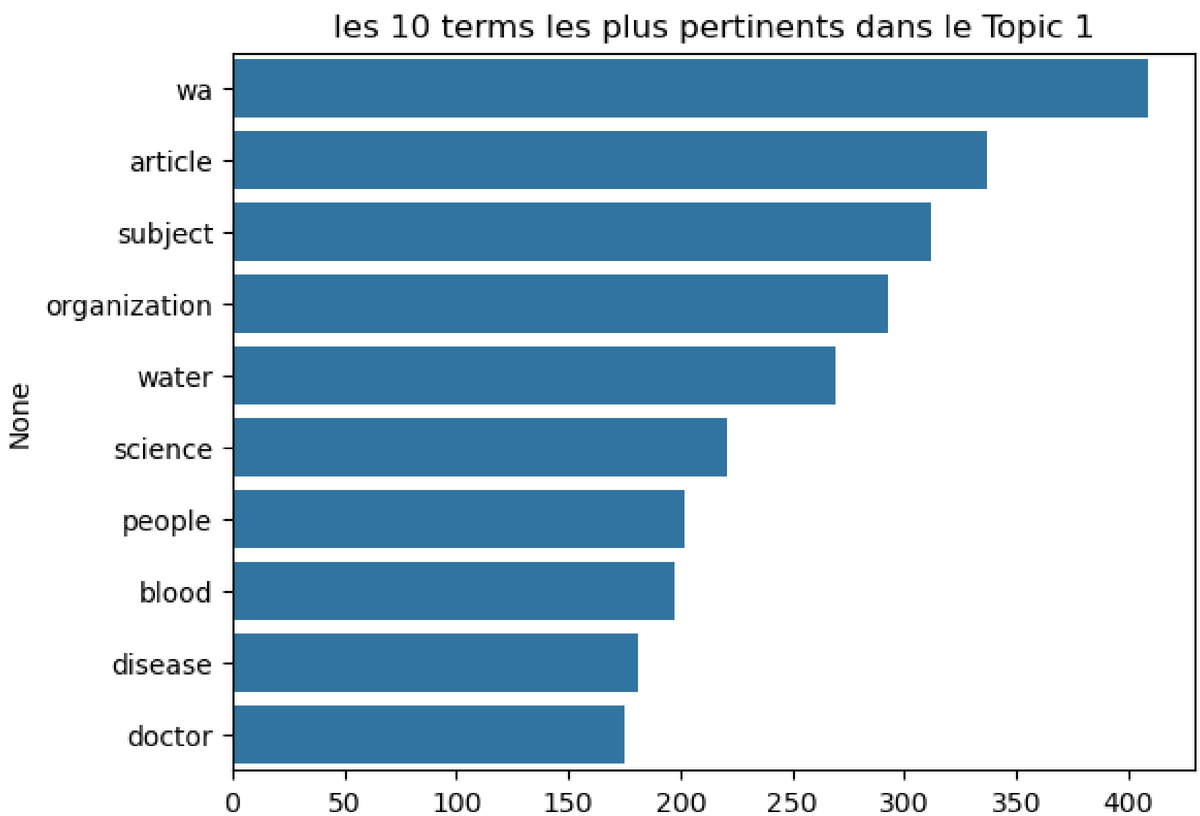
Visualisation

```
#Visualisation de la matrice theta des documents X topics

doc_topic_matrix=pd.DataFrame(data=theta, index = [f'Doc_{r}' for r in
range(0,theta.shape[0])], columns = [f'Topic_{r}' for r in
range(0,beta.T.shape[1])])
doc_topic_matrix
```

```
             Topic_0   Topic_1   Topic_2   Topic_3   Topic_4   Topic_5
\
Doc_0       0.001111  0.001111  0.001111  0.001111  0.852227  0.001111

Doc_1       0.000926  0.000926  0.000926  0.000926  0.200734  0.000926

Doc_2       0.000446  0.000446  0.000446  0.000446  0.166972  0.000446

Doc_3       0.001136  0.001136  0.001136  0.001136  0.001136  0.232909

Doc_4       0.000847  0.000847  0.375927  0.000847  0.000847  0.000847

...              ...       ...       ...       ...       ...       ...

Doc_11309   0.374837  0.000446  0.109150  0.000446  0.000446  0.000446

Doc_11310   0.001163  0.001163  0.001163  0.001163  0.001163  0.001163

Doc_11311   0.001087  0.001087  0.001087  0.001087  0.552786  0.001087

Doc_11312   0.000794  0.000794  0.000794  0.000794  0.000794  0.000794

Doc_11313   0.001667  0.035022  0.001667  0.001667  0.242278  0.136934
```

```
           Topic_6   Topic_7   Topic_8   Topic_9  Topic_10  Topic_11
\
Doc_0     0.001111  0.001111  0.001111  0.001111  0.001111  0.001111

Doc_1     0.000926  0.000926  0.000926  0.340623  0.000926  0.000926

Doc_2     0.024048  0.000446  0.039409  0.387229  0.060043  0.229052

Doc_3     0.001136  0.001136  0.001136  0.181281  0.001136  0.001136

Doc_4     0.000847  0.000847  0.000847  0.370528  0.000847  0.000847

...            ...       ...       ...       ...       ...       ...

Doc_11309 0.000446  0.000446  0.064789  0.099617  0.000446  0.147484

Doc_11310 0.001163  0.001163  0.070147  0.819305  0.001163  0.001163

Doc_11311 0.001087  0.001087  0.001087  0.147705  0.001087  0.001087

Doc_11312 0.000794  0.000794  0.000794  0.774602  0.000794  0.000794

Doc_11313 0.001667  0.001667  0.048369  0.001667  0.001667  0.001667


          Topic_12  Topic_13  Topic_14  Topic_15  Topic_16  Topic_17
\
Doc_0     0.001111  0.001111  0.001111  0.001111  0.001111  0.001111

Doc_1     0.000926  0.087475  0.000926  0.000926  0.177093  0.000926

Doc_2     0.087443  0.000446  0.000446  0.000446  0.000446  0.000446

Doc_3     0.001136  0.001136  0.001136  0.001136  0.042857  0.001136

Doc_4     0.000847  0.000847  0.000847  0.000847  0.000847  0.000847

...            ...       ...       ...       ...       ...       ...

Doc_11309 0.000446  0.000446  0.000446  0.197873  0.000446  0.000446

Doc_11310 0.001163  0.001163  0.001163  0.001163  0.001163  0.001163

Doc_11311 0.001087  0.001087  0.192454  0.089664  0.001087  0.001087

Doc_11312 0.000794  0.000794  0.000794  0.000794  0.000794  0.078264

Doc_11313 0.001667  0.001667  0.001667  0.001667  0.001667  0.001667


          Topic_18  Topic_19
```

```
Doc_0      0.127773  0.001111
Doc_1      0.180187  0.000926
Doc_2      0.000446  0.000446
Doc_3      0.524770  0.001136
Doc_4      0.000847  0.239138
...             ...       ...
Doc_11309  0.000446  0.000446
Doc_11310  0.001163  0.090781
Doc_11311  0.001087  0.001087
Doc_11312  0.000794  0.133643
Doc_11313  0.512397  0.001667

[11314 rows x 20 columns]

#affichage de la matrice beta des termes x Topics

term_topic_matrix=pd.DataFrame(data=beta.T, index =
vectorizer.get_feature_names_out(), columns = [f'Topic_{r}' for r in
range(0,beta.T.shape[1])])
term_topic_matrix


from matplotlib import pyplot as plt
import seaborn as sns

data = term_topic_matrix[f'Topic_0']
data = data.sort_values(ascending=False)
top_10 = data[:10]
title='les 10 terms les plus pertinents dans le Topic 1'
plt.title(title)
sns.barplot(x= top_10.values, y=top_10.index)



<Axes: title={'center': 'les 10 terms les plus pertinents dans le
Topic 1'}, ylabel='None'>
```




```
#
```

Exercice

- Realiser une visualisation globale des differentes topics decouverts pour la LSA et la LDA
- Appliquer le modèle unigrame language model pour decouvrir un topic par document

LDA

```
# %pip install pyLDAvis
import pyLDAvis
import pyLDAvis.gensim_models as gensimvis
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.decomposition import LatentDirichletAllocation
import numpy as np
import pandas as pd


data = pyLDAvis.prepare(
    topic_term_dists=lda.components_ / lda.components_.sum(axis=1)[:, 
np.newaxis],
    doc_topic_dists=lda.transform(vect),
    doc_lengths=[len(doc.split()) for doc in corpus_lemetized],
    vocab=vectorizer.get_feature_names_out(),
```

```
    term_frequency=np.array(vect.sum(axis=0)).flatten()
)

pyLDAvis.display(data)
```

```
<IPython.core.display.HTML object>
```

LSA

```
# Conversion de la matrice pour pyLDAvis
data = pyLDAvis.prepare(
    topic_term_dists=lda.components_ / lda.components_.sum(axis=1)[:, 
np.newaxis],
    doc_topic_dists=lda.transform(vect),
    doc_lengths=[len(doc.split()) for doc in corpus_lemetized],
    vocab=vectorizer.get_feature_names_out(),
    term_frequency=np.array(vect.sum(axis=0)).flatten()
)

pyLDAvis.display(data)
```

```
<IPython.core.display.HTML object>
```

Language ModelUnigramme

```
from collections import Counter
from sklearn.feature_extraction.text import CountVectorizer
import pandas as pd

vectorizer = CountVectorizer(stop_words='english')
doc_term_matrix = vectorizer.fit_transform(corpus_lemetized)
vocab = vectorizer.get_feature_names_out()

def unigram_language_model(doc_matrix, vocab, top_n=5):
    topics = []
    for doc_idx in range(doc_matrix.shape[0]):
        word_counts = doc_matrix[doc_idx].toarray().flatten()
        top_word_indices = word_counts.argsort()[-top_n:][::-1]
        top_words = [vocab[i] for i in top_word_indices]
        topics.append(top_words)
    return topics

document_topics = unigram_language_model(doc_term_matrix, vocab)

results = pd.DataFrame({
    'Document': [f"Document {i+1}" for i in 
range(len(corpus_lemetized))],
    'Topic Words': [' '.join(topic) for topic in document_topics]
})
```

```python
print("Topics par document :")
print(results)
```

```
Topics par document :
                 Document                              Topic Words
0              Document 1          car wa know university college
1              Document 2                 clock si poll speed guy
2              Document 3       display anybody doe computer don
3              Document 4       joe green computer chip division
4              Document 5     warning error known question launch
...                   ...                                     ...
11309     Document 11310    patient scan diagnosis headache brain
11310     Document 11311              mac new screen blank plus
11311     Document 11312        cooler mounting ended socket case
11312     Document 11313    sphere space graphics collins central
11313     Document 11314         number stolen help honda alumnus

[11314 rows x 2 columns]
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