Analyse des listes d'ingrédients et contenu des fiches techniques

Pierre Massé

June 11, 2020

1 Préambule

1.1 Imports

[1]:
```
# setting up sys.path for relative imports
from pathlib import Path
import sys
project_root = str(Path(sys.path[0]).parents[1].absolute())
if project_root not in sys.path:
    sys.path.append(project_root)
```

[201]:
```
# imports and customization of diplay
import os
from functools import partial
from collections import defaultdict
import re
import numpy as np
from scipy.stats import linregress
import pandas as pd
pd.options.display.min_rows = 6
pd.options.display.width=108
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.base import clone
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score, cross_validate
from sklearn.pipeline import Pipeline
from sklearn.decomposition import TruncatedSVD
from sklearn.decomposition import PCA
from sklearn.manifold import Isomap
from sklearn.preprocessing import StandardScaler
from gensim.models import word2vec

from matplotlib import pyplot as plt
import matplotlib.patches as mpatch
import matplotlib.cm as cm
import matplotlib.colors as colors
from matplotlib.colors import Normalize
import matplotlib.ticker as mtick
import seaborn as sns

from src.pimest import ContentGetter
from src.pimest import PathGetter
from src.pimest import PDFContentParser
from src.pimest import BlockSplitter
from src.pimest import SimilaritySelector
from src.pimest import custom_accuracy
from src.pimest import text_sim_score
from src.pimest import text_similarity
from src.pimest import build_text_processor
```

1.2 Acquisition des données de la ground truth

[4]:
```
ground_truth_df = pd.read_csv(Path('..') / '..' / 'ground_truth' / 'manually_labelled_ground_truth.csv',
                              sep=';',
                              encoding='latin-1',
                              index_col='uid')
ground_truth_uids = list(ground_truth_df.index)

acqui_pipe = Pipeline([('PathGetter', PathGetter(ground_truth_uids=ground_truth_uids,
                                                  train_set_path=Path('..') / '..' / 'ground_truth',
```

```
                                                  ground_truth_path=Path('..') / '..' / 'ground_truth',
                                                  )),
                         ('ContentGetter', ContentGetter(missing_file='to_nan')),
                         ('ContentParser', PDFContentParser(none_content='to_empty')),
                        ],
                        verbose=True)

texts_df = acqui_pipe.fit_transform(ground_truth_df)
texts_df['ingredients'] = texts_df['ingredients'].fillna('')
texts_df
```

```
[Pipeline] … (step 1 of 3) Processing PathGetter, total=   0.1s
[Pipeline] … (step 2 of 3) Processing ContentGetter, total=   0.1s
Launching 8 processes.
[Pipeline] … (step 3 of 3) Processing ContentParser, total=  39.1s
```

[4]:

```
                                                                     designation  \
uid
a0492df6-9c76-4303-8813-65ec5ccbfa70   Concentré liquide Asian en bouteille 980 ml CHEF
d183e914-db2f-4e2f-863a-a3b2d054c0b8             Pain burger curry 80 g CREATIV BURGER
ab48a1ed-7a3d-4686-bb6d-ab4f367cada8                  Macaroni en sachet 500 g PANZANI
…                                                                                   …
e67341d8-350f-46f4-9154-4dbbb8035621             PRÉPARATION POUR CRÈME BRÛLÉE BIO 6L
a8f6f672-20ac-4ff8-a8f2-3bc4306c8df3  Céréales instantanées en poudre saveur caramel…
0faad739-ea8c-4f03-b62e-51ee592a0546                          FARINE DE BLÉ TYPE 45, 10KG

                                                                     ingredients  \
uid
a0492df6-9c76-4303-8813-65ec5ccbfa70  Eau, maltodextrine, sel, arômes, sucre, arôme …
d183e914-db2f-4e2f-863a-a3b2d054c0b8  Farine de blé T65, eau, levure, vinaigre de ci…
ab48a1ed-7a3d-4686-bb6d-ab4f367cada8  - 100% Semoule de BLE dur de qualité supérieur…
…                                                                                   …
e67341d8-350f-46f4-9154-4dbbb8035621  Sucre roux de canne*° (64%), amidon de maïs*, …
a8f6f672-20ac-4ff8-a8f2-3bc4306c8df3  Farine 87,1 % (Blé (GLUTEN), Blé hydrolysé (GL…
0faad739-ea8c-4f03-b62e-51ee592a0546                                  Farine de blé T45

                                                                            path  \
uid
a0492df6-9c76-4303-8813-65ec5ccbfa70  ../../ground_truth/a0492df6-9c76-4303-8813-65e…
d183e914-db2f-4e2f-863a-a3b2d054c0b8  ../../ground_truth/d183e914-db2f-4e2f-863a-a3b…
ab48a1ed-7a3d-4686-bb6d-ab4f367cada8  ../../ground_truth/ab48a1ed-7a3d-4686-bb6d-ab4…
…                                                                                   …
e67341d8-350f-46f4-9154-4dbbb8035621  ../../ground_truth/e67341d8-350f-46f4-9154-4db…
a8f6f672-20ac-4ff8-a8f2-3bc4306c8df3  ../../ground_truth/a8f6f672-20ac-4ff8-a8f2-3bc…
0faad739-ea8c-4f03-b62e-51ee592a0546  ../../ground_truth/0faad739-ea8c-4f03-b62e-51e…

                                                                         content  \
uid
a0492df6-9c76-4303-8813-65ec5ccbfa70  b'%PDF-1.5\r\n%\xb5\xb5\xb5\xb5\r\n1 0 obj\r\n…
d183e914-db2f-4e2f-863a-a3b2d054c0b8  b'%PDF-1.5\r%\xe2\xe3\xcf\xd3\r\n4 0 obj\r<</L…
ab48a1ed-7a3d-4686-bb6d-ab4f367cada8  b'%PDF-1.4\n%\xc7\xec\x8f\xa2\n5 0 obj\n<</Len…
…                                                                                   …
e67341d8-350f-46f4-9154-4dbbb8035621  b'%PDF-1.7\r\n%\xb5\xb5\xb5\xb5\r\n1 0 obj\r\n…
a8f6f672-20ac-4ff8-a8f2-3bc4306c8df3  b'%PDF-1.5\r\n%\xb5\xb5\xb5\xb5\r\n1 0 obj\r\n…
0faad739-ea8c-4f03-b62e-51ee592a0546  b'%PDF-1.5\r\n%\xb5\xb5\xb5\xb5\r\n1 0 obj\r\n…

                                                                            text
uid
a0492df6-9c76-4303-8813-65ec5ccbfa70  Concentré Liquide Asian CHEF® \n\nBouteille de…
d183e914-db2f-4e2f-863a-a3b2d054c0b8

ab48a1ed-7a3d-4686-bb6d-ab4f367cada8  Direction Qualité \n\n \n\n \n\nPATES ALIMENTA…
…                                                                                   …
e67341d8-350f-46f4-9154-4dbbb8035621  FICHE TECHNIQUE \n\nCREME BRÛLÉE 6L \n\nREF : …
a8f6f672-20ac-4ff8-a8f2-3bc4306c8df3  81 rue de Sans Souci - CS13754 - 69576 Limones…
0faad739-ea8c-4f03-b62e-51ee592a0546   \n1050/10502066400 \n\n10502055300/1050202520…

[500 rows x 5 columns]
```

On fusionne les corpus

[5]:

```
target_df = texts_df['ingredients'].rename('text').to_frame()
target_df.loc[:, 'source'] = 'target'
content_df = texts_df['text'].to_frame()
content_df['source'] = 'content'
corpus_df = pd.concat([target_df, content_df])
corpus_df = corpus_df.reset_index().set_index(['source', 'uid'])
corpus_df['text'].fillna('', inplace=True)
```

```
corpus_df
```

[5]:

```
                                                                                     text
source  uid
target  a0492df6-9c76-4303-8813-65ec5ccbfa70  Eau, maltodextrine, sel, arômes, sucre, arôme …
        d183e914-db2f-4e2f-863a-a3b2d054c0b8  Farine de blé T65, eau, levure, vinaigre de ci…
        ab48a1ed-7a3d-4686-bb6d-ab4f367cada8  - 100% Semoule de BLE dur de qualité supérieur…
…                                                                                          …
content e67341d8-350f-46f4-9154-4dbbb8035621  FICHE TECHNIQUE \n\nCREME BRÛLÉE 6L \n\nREF : …
        a8f6f672-20ac-4ff8-a8f2-3bc4306c8df3  81 rue de Sans Souci - CS13754 - 69576 Limones…
        0faad739-ea8c-4f03-b62e-51ee592a0546   \n1050/10502066400 \n\n10502055300/1050202520…

[1000 rows x 1 columns]
```

2 Analyses

2.1 Analyse des longueurs des textes

[6]:

```
lengths = corpus_df['text'].apply(len)
print(
lengths.reset_index()
        .groupby('source')
        .describe()
        .rename({'content': 'Texte des documents',
                 'target': "Listes d'ingrédients"})
        .to_latex(#Path('..') / 'tbls' / 'text_lengths.tex',
                  bold_rows=True,
                  column_format='lcccccccc',
                  index_names=False,
                 )
)
lengths.reset_index().groupby('source').describe()
```

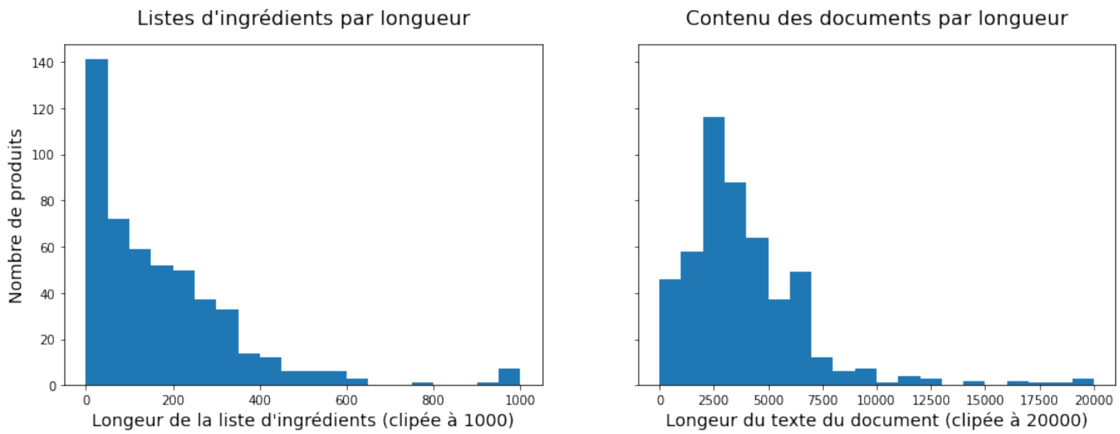
```
\begin{tabular}{lcccccccc}
\toprule
{} & \multicolumn{8}{l}{text} \\
{} &  count &      mean &          std &  min &      25\% &     50\% &      75\% &      max \\
\midrule
\textbf{Texte des documents } &  500.0 &  3937.630 &  3280.860732 &  0.0 &  2173.75 &  3247.5 &  5034.25 &
37322.0 \\
\textbf{Listes d'ingrédients} &  500.0 &   199.686 &   457.044723 &  0.0 &    43.00 &   122.0 &   250.75 &
7963.0 \\
\bottomrule
\end{tabular}
```

[6]:

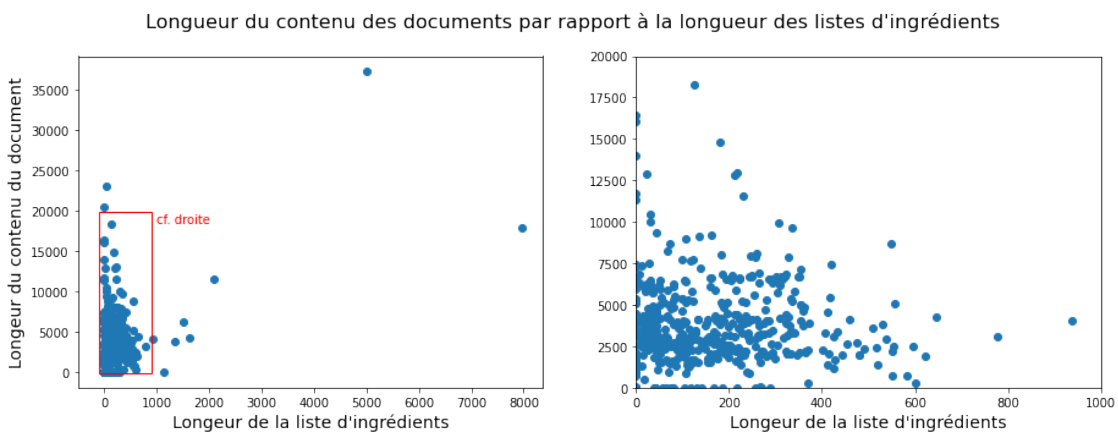
	text							
	count	mean	std	min	25%	50%	75%	max
source								
content	500.0	3937.630	3280.860732	0.0	2173.75	3247.5	5034.25	37322.0
target	500.0	199.686	457.044723	0.0	43.00	122.0	250.75	7963.0

[7]:

```
fig, axs = plt.subplots(ncols=2, figsize=(15, 5), sharey=True)
axs[0].hist(lengths.loc['target'].clip(0, 1000), bins=20)
axs[0].set_title("Listes d'ingrédients par longueur", fontsize=16, pad=15)
axs[0].set_ylabel("Nombre de produits", fontsize=14)
axs[0].set_xlabel("Longeur de la liste d'ingrédients (clipée à 1000)", fontsize=14)
axs[1].hist(lengths.loc['content'].clip(0, 20000), bins=20)
axs[1].set_title("Contenu des documents par longueur", fontsize=16, pad=15)
axs[1].set_xlabel("Longeur du texte du document (clipée à 20000)", fontsize=14)
# fig.savefig(Path('..') / 'img' / 'text_lengths.png', bbox_inches='tight')
```



[8]:
```python
fig, axs = plt.subplots(ncols=2, figsize=(15, 5))

axs[0].scatter(x=lengths.loc['target'], y=lengths.loc['content'])
axs[0].set_xlabel("Longeur de la liste d'ingrédients", fontsize=14)
axs[0].set_ylabel("Longeur du contenu du document", fontsize=14)
axs[0].add_patch(mpatch.Rectangle((-100, -150), 1000, 20000, fill=False, color='red'))
axs[0].annotate('cf. droite', (1000, 18500), color='red')
axs[1].scatter(x=lengths.loc['target'], y=lengths.loc['content'])
axs[1].set_xlabel("Longeur de la liste d'ingrédients", fontsize=14)
axs[1].set_xlim(0, 1000)
axs[1].set_ylim(0, 20000)
fig.suptitle("Longueur du contenu des documents par rapport à la longueur des listes d'ingrédients", fontsize=16)
# fig.savefig(Path('..') / 'img' / 'text_lengths_2.png', bbox_inches='tight')
```



[9]:
```python
linregress(x=lengths.loc['target'], y=lengths.loc['content']).rvalue ** 2
```

[9]: 0.139326761283587

2.2 Analyse des mots

[76]:
```python
stop_words = {'de', 'et', 'la', 'en', 'du', 'les', 'des', 'le', 'dans', 'ce', 'un', 'pour',
              'par', 'sur', 'au', 'dont', 'of', 'and', 'pas', 'est', 'ou', 'que'}
print(stop_words)
```

```
{'par', 'pas', 'dans', 'des', 'les', 'pour', 'ce', 'est', 'de', 'of', 'un', 'and', 'la', 'sur', 'du', 'en',
'au', 'ou', 'et', 'que', 'dont', 'le'}
```

[11]:
```
tfidf_corpus = TfidfVectorizer(strip_accents='unicode',
                               lowercase=True,
                               stop_words=stop_words,
                               ngram_range=(1, 1),
                               max_df=1.0,
                               #min_df=0.0, A TESTER !
                               binary=False,
                               norm=None, # set to l1 or l2
                               use_idf=False,
                               smooth_idf=False,
                               sublinear_tf=False,
                              )
vectorized_corpus = tfidf_corpus.fit_transform(corpus_df['text'])
tokenizer = tfidf_corpus.build_analyzer()
```

Comptage des mots du vocabulaire du corpus :

[12]:
```
inverse_corpus_voc = {val: key for key, val in tfidf_corpus.vocabulary_.items()}
word_counts = np.asarray(vectorized_corpus.sum(axis=0)).squeeze()
print(f'Corpus vocabulary size is ', len(tfidf_corpus.vocabulary_), '\n')
print('Most frequent words in vocabulary are:')
most_freq = dict()
for idx in word_counts.argsort()[::-1][:20]:
    most_freq[inverse_corpus_voc[idx].ljust(12)] = int(word_counts[idx])
    print(f'{inverse_corpus_voc[idx].ljust(12)}: {word_counts[idx]:5} occurences')

str_cpt_corpus = [f'{word.ljust(12)}: {most_freq[word]} occurences \\\\' for word in most_freq.keys()]
```

```
Corpus vocabulary size is  15465

Most frequent words in vocabulary are:
produit     : 2198.0 occurences
non         : 2164.0 occurences
produits    : 1508.0 occurences
10          : 1404.0 occurences
kg          : 1290.0 occurences
base        : 1119.0 occurences
sel         : 1041.0 occurences
poids       : 1021.0 occurences
100         : 971.0 occurences
palette     : 933.0 occurences
ingredients : 917.0 occurences
date        : 904.0 occurences
sucre       : 841.0 occurences
12          : 803.0 occurences
code        : 801.0 occurences
lait        : 733.0 occurences
absence     : 697.0 occurences
fiche       : 688.0 occurences
the         : 658.0 occurences
france      : 657.0 occurences
```

Constitution du vocabulaire des listes d'ingrédients

[13]:
```
tfidf_ingred = clone(tfidf_corpus)
vectorized_ingred = tfidf_ingred.fit_transform(corpus_df.loc['target', 'text'])
```

[14]:
```
inverse_ingred_voc = {val: key for key, val in tfidf_ingred.vocabulary_.items()}
word_counts = np.asarray(vectorized_ingred.sum(axis=0)).squeeze()
print(f'Ingredient vocabulary size is ', len(tfidf_ingred.vocabulary_), '\n')
print('Most frequent words in vocabulary are:')
most_freq = dict()
for idx in word_counts.argsort()[::-1][:20]:
    most_freq[inverse_ingred_voc[idx].ljust(12)] = int(word_counts[idx])
    print(f'{inverse_ingred_voc[idx].ljust(10)}: {word_counts[idx]:5} occurences')

str_cpt_corpus_2 = [f'{word.ljust(12)}: {most_freq[word]} occurences &' for word in most_freq.keys()]
str_latex = '\n'.join([str2 + ' ' + str1 for str1, str2 in zip(str_cpt_corpus, str_cpt_corpus_2)])
#print(str_latex)
```

```
Ingredient vocabulary size is  1324

Most frequent words in vocabulary are:
sucre     : 363.0 occurences
acide     : 255.0 occurences
sel       : 240.0 occurences
sirop     : 180.0 occurences
eau       : 178.0 occurences
```

```
poudre    : 176.0 occurences
arome     : 175.0 occurences
lait      : 171.0 occurences
ble       : 171.0 occurences
huile     : 146.0 occurences
citrique  : 132.0 occurences
farine    : 128.0 occurences
amidon    : 125.0 occurences
glucose   : 124.0 occurences
cacao     : 122.0 occurences
extrait   : 117.0 occurences
acidifiant: 114.0 occurences
aromes    :  98.0 occurences
soja      :  96.0 occurences
concentre :  92.0 occurences
```

On vérifie s'il existe des mots qui sont inclus dans les listes d'ingrédients mais pas dans les documents :

[15]:
```
ingred_only = {word for word in tfidf_ingred.vocabulary_ if word not in tfidf_corpus.vocabulary_}
ingred_only
```

[15]:
```
set()
```

Constitution d'une nouvelle feature qui sont les textes tokenisés via la méthode du CountVectorizer.

[16]:
```
corpus_df['tokenized'] = corpus_df['text'].apply(tokenizer)
corpus_df
```

[16]:
```
                                                                                   text  \
source  uid
target  a0492df6-9c76-4303-8813-65ec5ccbfa70  Eau, maltodextrine, sel, arômes, sucre, arôme …
        d183e914-db2f-4e2f-863a-a3b2d054c0b8  Farine de blé T65, eau, levure, vinaigre de ci…
        ab48a1ed-7a3d-4686-bb6d-ab4f367cada8  - 100% Semoule de BLE dur de qualité supérieur…
…                                                                                   …
content e67341d8-350f-46f4-9154-4dbbb8035621  FICHE TECHNIQUE \n\nCREME BRÛLÉE 6L \n\nREF : …
        a8f6f672-20ac-4ff8-a8f2-3bc4306c8df3  81 rue de Sans Souci - CS13754 - 69576 Limones…
        0faad739-ea8c-4f03-b62e-51ee592a0546   \n1050/10502066400 \n\n10502055300/1050202520…

                                                                              tokenized
source  uid
target  a0492df6-9c76-4303-8813-65ec5ccbfa70  [eau, maltodextrine, sel, aromes, sucre, arome…
        d183e914-db2f-4e2f-863a-a3b2d054c0b8  [farine, ble, t65, eau, levure, vinaigre, cidr…
        ab48a1ed-7a3d-4686-bb6d-ab4f367cada8  [100, semoule, ble, dur, qualite, superieure, …
…                                                                                   …
content e67341d8-350f-46f4-9154-4dbbb8035621  [fiche, technique, creme, brulee, 6l, ref, nap…
        a8f6f672-20ac-4ff8-a8f2-3bc4306c8df3  [81, rue, sans, souci, cs13754, 69576, limones…
        0faad739-ea8c-4f03-b62e-51ee592a0546  [1050, 10502066400, 10502055300, 10502025200, …

[1000 rows x 2 columns]
```

3 Analyse de données

4 Représentation des mots

4.1 Document frequency

1- Déjà, on calcule une métrique qui permet de dire si un mot est plutôt un mot de type ingrédients ou un mot issu du corpus.

Représentation simple : on regarde simplement la document frequency de chacun des mots dans le corpus des ingrédients.

[17]:
```
doc_freq_counter = clone(tfidf_ingred)
doc_freq_counter.set_params(binary=True).fit(corpus_df.loc['target', 'text'])
binary_ingred_counts = doc_freq_counter.transform(corpus_df.loc[:, 'text'])
```

[18]:
```
doc_freq_ingred = binary_ingred_counts[:500]
doc_freq_ingred = np.array(doc_freq_ingred.sum(axis=0)).reshape(-1) / 500
print('shape of doc_freq_ingred :', doc_freq_ingred.shape)
doc_freq_ingred_translator = defaultdict(lambda: 0., {word: doc_freq_ingred[tfidf_ingred.vocabulary_[word]]
                              for word in tfidf_ingred.vocabulary_.keys()})

print(doc_freq_ingred_translator['sucre'])
print(doc_freq_ingred_translator['taboullllleeeeeeeiiiiiii'])
print(doc_freq_ingred_translator['maltodextrine'])
```

```
shape of doc_freq_ingred : (1324,)
0.448
0.0
0.064
```

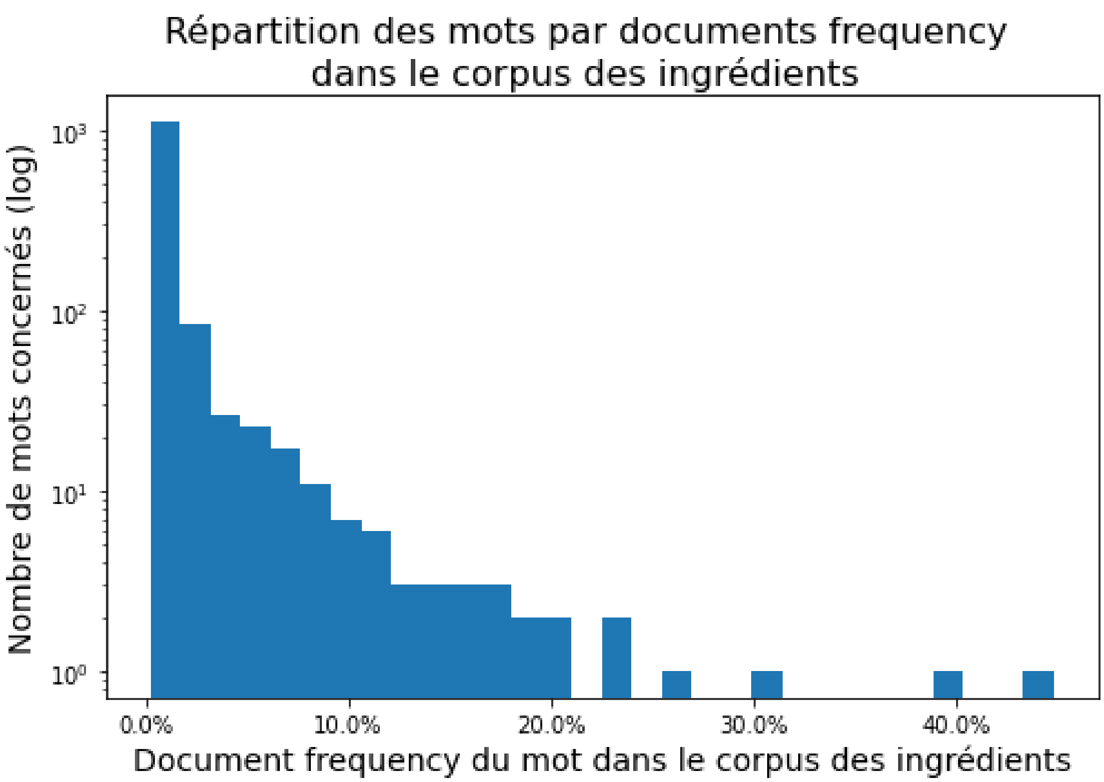
On constitue un array qui nous servira plus tard, avec le document frequency dans les ingrédients de tous les mots utilisés dans le contenu des documents.

[19]:
```
corpus_doc_freq_ingred = np.zeros(shape=(len(tfidf_corpus.vocabulary_)))
for i in range(len(tfidf_corpus.vocabulary_)):
    corpus_doc_freq_ingred[i] = doc_freq_ingred_translator[inverse_corpus_voc[i]]
corpus_doc_freq_ingred
```

[19]:
```
array([0.004, 0.   , 0.   , …, 0.   , 0.   , 0.   ])
```

On peut sortir les top scorer de la doc frequency :

[28]:
```
fig, ax = plt.subplots(figsize=(8, 5))
ax.hist(doc_freq_ingred, bins=30, log=True)
ax.xaxis.set_major_formatter(mtick.PercentFormatter(xmax=1.))
ax.set_xlabel("Document frequency du mot dans le corpus des ingrédients", fontsize=14)
ax.set_ylabel("Nombre de mots concernés (log)", fontsize=14)
fig.suptitle("Répartition des mots par documents frequency\ndans le corpus des ingrédients", fontsize=16)
# fig.savefig(Path('..') / 'img' / 'doc_freq_of_ingreds.png', bbox_inches='tight')
```



[22]:
```
for word_idx in doc_freq_ingred.argsort()[::-1][:20]:
    print(inverse_ingred_voc[word_idx], '&', f'{doc_freq_ingred[word_idx]*100:.2f}\\%', '\\\\')

for word_idx in doc_freq_ingred.argsort()[:20]:
    print(inverse_ingred_voc[word_idx], '&', f'{doc_freq_ingred[word_idx]*100:.2f}\\%', '\\\\')
```

```
sucre & 44.80\% \\
sel & 40.00\% \\
eau & 30.20\% \\
acide & 26.20\% \\
arome & 23.00\% \\
huile & 23.00\% \\
```

```
ble & 20.60\% \\
amidon & 20.00\% \\
aromes & 19.00\% \\
sirop & 18.40\% \\
citrique & 18.00\% \\
lait & 17.20\% \\
acidifiant & 17.00\% \\
farine & 16.40\% \\
extrait & 16.20\% \\
glucose & 16.00\% \\
concentre & 14.80\% \\
jus & 14.00\% \\
poudre & 14.00\% \\
colza & 13.20\% \\
ferrique & 0.20\% \\
d3 & 0.20\% \\
datte & 0.20\% \\
dattes & 0.20\% \\
debris & 0.20\% \\
decafeine & 0.20\% \\
deciree & 0.20\% \\
deconseille & 0.20\% \\
nectar & 0.20\% \\
necessaire & 0.20\% \\
ne & 0.20\% \\
delta & 0.20\% \\
naturelles & 0.20\% \\
denoyautees & 0.20\% \\
dentier & 0.20\% \\
depellicule & 0.20\% \\
cysteine & 0.20\% \\
negra & 0.20\% \\
new & 0.20\% \\
nicotinamide & 0.20\% \\
```

[309]:
```
# looking for first word in documents but not in ingredients
for word_idx in np.array(vectorized_corpus[500:].sum(axis=0)).reshape(15465).argsort()[::-1]:
    print(inverse_corpus_voc[word_idx])
    if inverse_corpus_voc[word_idx] not in tfidf_ingred.vocabulary_:
        print('trouvé !')
        break
```

```
produit
non
produits
10
kg
base
poids
trouvé !
```

[75]:
```
ingred_scores.shape
```

[75]:
```
(1324,)
```

[291]:
```
ingred_scores = np.log2(doc_freq_ingred * 500 + 1)
sample = doc_freq_ingred.argsort()[::-1][[0, 10, 100, 250, 702]]
sample_scores = ingred_scores[sample]
labels = [inverse_ingred_voc[word_idx] + f'\n{ingred_scores[word_idx]:.2f}' for word_idx in sample] + ['poids\n0.00']
labels
```

[291]:
```
['sucre\n7.81',
 'citrique\n6.51',
 'issus\n4.39',
 'si\n2.81',
 'plantations\n1.58',
 'poids\n0.00']
```

[292]:
```
gradient = np.linspace(0, 8, 256)
gradient = np.vstack((gradient, gradient, gradient ))


fig, ax = plt.subplots(figsize=(8, 3))

ax.imshow(gradient, aspect=3, cmap='seismic', vmin=-8, vmax=8)
ax.set_xticks(np.hstack((255 / 8 * sample_scores, np.array([0]))))
```

```
ax.set_xticklabels(labels, fontsize = 12)
#ax.set_xlim(0, 50)
ax.set_yticks([])
# fig.savefig(Path('..') / 'img' / 'scores_bar.png', bbox_inches='tight')
```

[292]: []

On calcule les document frequencies des mots issus des documents, et on compte sur les corpus.

[293]:
```
doc_freq_counter_2 = clone(tfidf_corpus)
doc_freq_counter_2.set_params(binary=False).fit(corpus_df.loc[: , 'text'])
word_counts = np.array(doc_freq_counter_2.transform(corpus_df.loc[:, 'text']).todense())
delta_doc_counts = (word_counts[500:] - word_counts[:500])
binary_delta = np.where(delta_doc_counts > 0., np.ones(delta_doc_counts.shape), np.zeros(delta_doc_counts.shape))
docs_scores = np.log2(binary_delta.sum(axis=0) + 1)
```

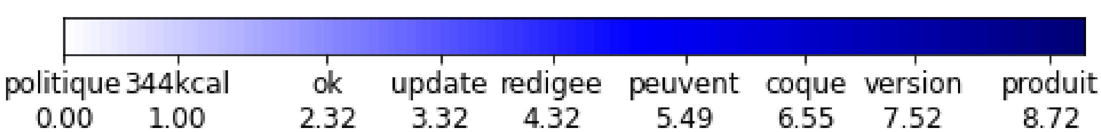
[294]:
```
docs_scores[tfidf_corpus.vocabulary_['produits']]
```

[294]: 8.005624549193879

[295]:
```
sample = docs_scores.argsort()[::-1][[0, 90, 251, 550, 1200, 2200, 3803, 10005]]
sample_scores = docs_scores[sample]
labels = [inverse_corpus_voc[word_idx] + f'\n{docs_scores[word_idx]:.2f}' for word_idx in sample]
labels
```

[295]:
```
['produit\n8.72',
 'version\n7.52',
 'coque\n6.55',
 'peuvent\n5.49',
 'redigee\n4.32',
 'update\n3.32',
 'ok\n2.32',
 '344kcal\n1.00']
```

[298]:
```
gradient = np.linspace(0, 8, 256)
gradient = np.vstack((gradient, gradient, gradient ))

fig, ax = plt.subplots(figsize=(8, 3))

ax.imshow(gradient, aspect=3, cmap='seismic_r', vmin=-9, vmax=9)
ax.set_xticks(np.hstack((255 / 9 * sample_scores, np.array([0]))))
ax.set_xticklabels(labels + ["politique\n0.00"], fontsize = 12)
#ax.set_xlim(0, 50)
ax.set_yticks([])
# fig.savefig(Path('..') / 'img' / 'corpus_score_bar.png', bbox_inches='tight')
```



Et maintenant on calcule le score relatif de chacun des mots.

[299]:
```
# new computation on ingredients, on corpus vocabulary indexing
binary_ingred = np.where(word_counts[:500] > 0., np.ones(word_counts[:500].shape), np.zeros(word_counts[:500].shape))
ingred_scores = np.log2(binary_ingred.sum(axis=0) + 1)
# check computation is coherent
print(ingred_scores[tfidf_corpus.vocabulary_['sucre']])
```

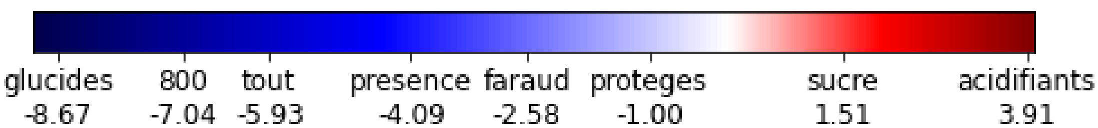
7.813781191217037

[300]:
```python
sample = np.hstack([relative_scores.argsort()[[0, 90, 251, 1200, 3000, 8007,  15464]], [14079]])
sample_scores = relative_scores[sample]
labels = [inverse_corpus_voc[word_idx] + f'\n{relative_scores[word_idx]:.2f}' for word_idx in sample]
labels
```

[300]:
```
['glucides\n-8.67',
 '800\n-7.04',
 'tout\n-5.93',
 'presence\n-4.09',
 'faraud\n-2.58',
 'proteges\n-1.00',
 'acidifiants\n3.91',
 'sucre\n1.51']
```

[301]:
```python
mmin, mmax, resolution = -9, 4, 1000
divnorm = colors.TwoSlopeNorm(vmin=mmin, vcenter=0, vmax=mmax)
gradient = np.linspace(mmin, mmax, resolution)
gradient = np.vstack([gradient, gradient])
# gradient = np.vstack([sorted(relative_scores), sorted(relative_scores)])

def convert_to_width(num):
    return(int(resolution * (num - mmin) / (mmax - mmin)))

fig, ax = plt.subplots(figsize=(8, 3))

ax.imshow(gradient, aspect=20, cmap='seismic', norm=divnorm ) #, vmin=-9, vmax=9)
ax.set_xticks(list(map(convert_to_width, sample_scores)))
# ax.set_xticks(255 / 18 * sample_scores)
ax.set_xticklabels(labels, fontsize = 12)
#ax.set_xlim(0, 50)
ax.set_yticks([])
# fig.savefig(Path('..') / 'img' / 'relative_score_bar.png', bbox_inches='tight')
```

[301]: []



4.2 Word embedings

4.2.1 Word2Vec

On calcule les embeddings avec Word2Vec

[302]:
```python
word2vec_model = word2vec.Word2Vec(corpus_df['tokenized'], min_count=1)
```

[303]:
```python
for i, word in enumerate(tfidf_corpus.vocabulary_.keys()):
    print('--------------------\n', word, ':', word2vec_model.wv[word][:5])
    if i > 4:
        break
```

```
--------------------
 eau : [-1.0830716  -0.46610487 -0.43349764  0.55493397  1.1007366 ]
--------------------
 maltodextrine : [ 0.01011625  0.15969634 -0.67031556  0.5559474   0.4602319 ]
--------------------
 sel : [-0.8459699  -0.21097712 -0.6416249   0.84254736  0.9729415 ]
--------------------
 aromes : [ 0.22419034  0.23973037 -1.4658073   1.1386586   1.0591131 ]
--------------------
 sucre : [-0.74801284  0.1217097  -2.0248985   1.5143404   1.4470899 ]
--------------------
 arome : [ 0.08999626  0.10789929 -2.2472398   1.5559452   1.5740927 ]
```

[265]:
```
ndarray_words_embeddings = np.vstack([word2vec_model.wv[inverse_corpus_voc[i]]
                                      for i in range(len(tfidf_corpus.vocabulary_))])
ndarray_words_embeddings
```

[265]:
```
array([[-1.9143574e+00, -1.0786384e+00, -1.6952591e+00, …,
         2.1197143e-04,  6.8014598e-01, -9.4786072e-01],
       [-1.0596310e+00, -5.1570371e-02, -2.4971814e+00, …,
        -4.9154687e-01,  1.3782319e+00, -1.2871372e+00],
       [-2.1143033e-01, -1.3124047e-01, -2.7956560e-01, …,
        -6.6144560e-03,  1.6432673e-02, -5.8027157e-03],
       …,
       [-4.8991539e-02, -1.6540296e-02, -6.0264323e-02, …,
         3.1673540e-03, -9.9934675e-03, -1.2510464e-02],
       [-8.2935727e-01, -6.4514387e-01, -8.7146807e-01, …,
        -1.7320616e-02,  3.3239821e-01, -3.0926281e-01],
       [-2.5584301e-01, -1.5305966e-01, -5.1036954e-01, …,
        -1.5918270e-02, -3.0415934e-02, -2.4762219e-01]], dtype=float32)
```

On effectue une PCA :

[266]:
```
scaled_words_embeddings = StandardScaler().fit_transform(ndarray_words_embeddings)
scaled_words_embeddings
```

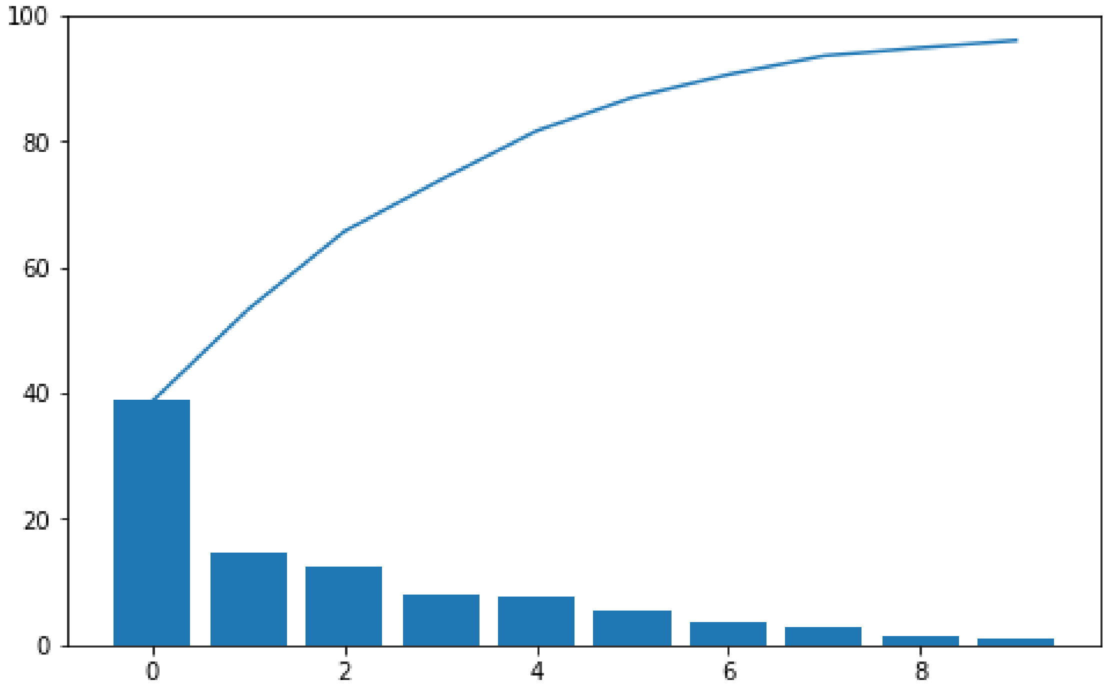
[266]:
```
array([[-10.750973  ,  -7.621986  ,  -6.1712112 , …,   0.1407848 ,
          4.966931  ,  -4.985649  ],
       [ -5.818584  ,  -0.29638907,  -9.341663  , …,  -5.478642  ,
          9.752907  ,  -6.8654494 ],
       [ -0.92385375,  -0.8646387 ,  -0.5741748 , …,   0.06277785,
          0.4166085 ,   0.23393212],
       …,
       [  0.01353529,  -0.04653592,   0.29284707, …,   0.17455655,
          0.23543474,   0.19676708],
       [ -4.489738  ,  -4.5300717 ,  -2.9142997 , …,  -0.05956358,
          2.5828223 ,  -1.4474237 ],
       [ -1.180147  ,  -1.0202649 ,  -1.4866732 , …,  -0.04353869,
          0.09542128,  -1.1058966 ]], dtype=float32)
```

[267]:
```
PCA_model = PCA(n_components=10)
PCA_words_embeddings = PCA_model.fit_transform(scaled_words_embeddings)
print(PCA_words_embeddings.shape)
```

```
(15465, 10)
```

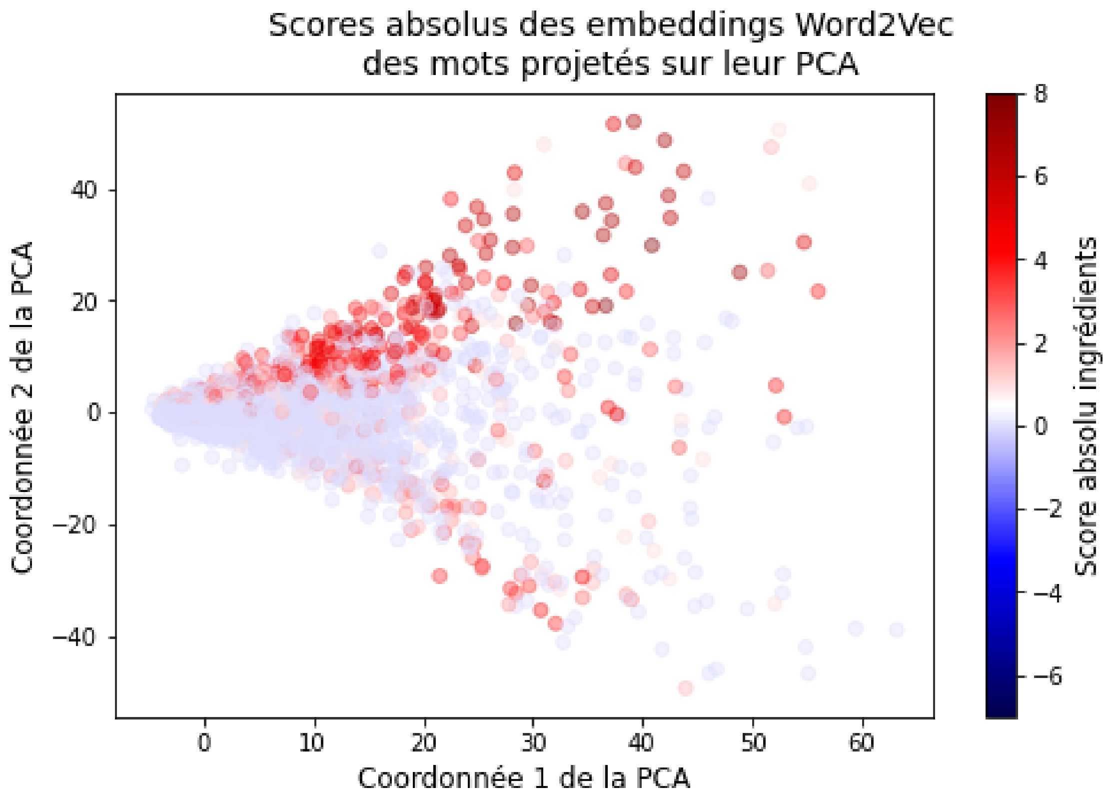
[268]:
```
fig, ax = plt.subplots(figsize=(8, 5))
ax.plot(PCA_model.explained_variance_ratio_.cumsum()*100)
ax.bar(x=range(10), height=PCA_model.explained_variance_ratio_*100)
ax.set_ylim(0, 100)
```

[268]:
```
(0.0, 100.0)
```



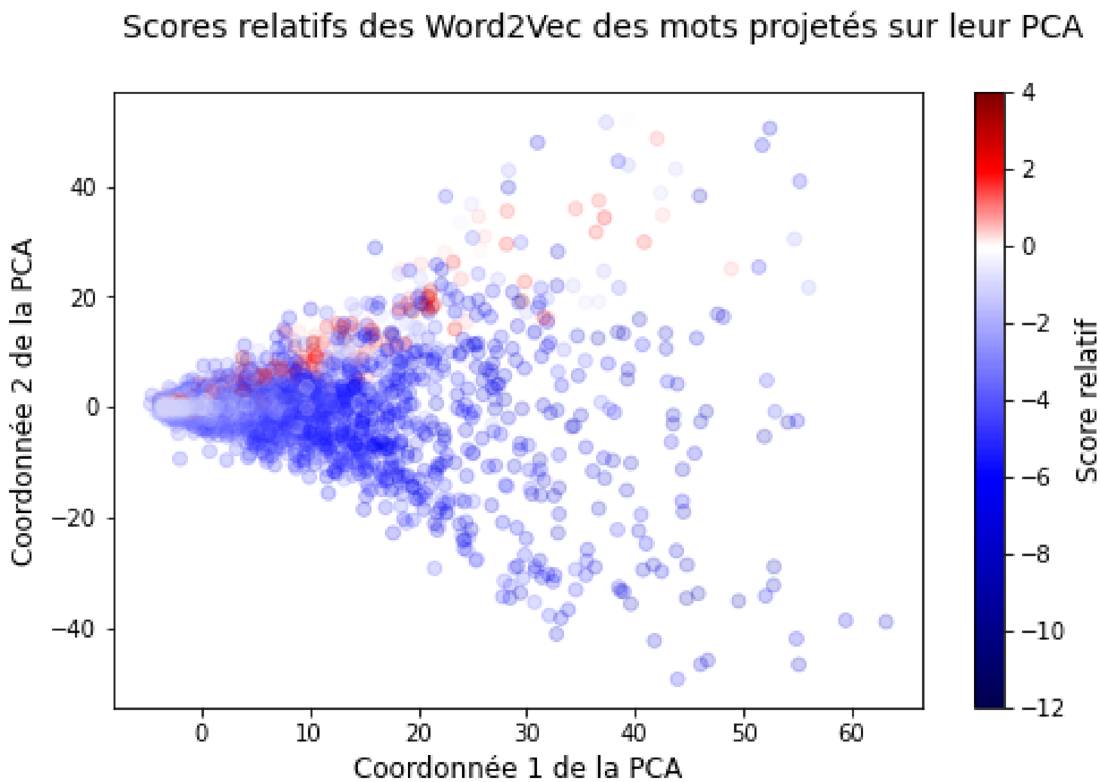
On la dessine :

[304]:
```
fig, ax = plt.subplots(figsize=(8, 5))
scat = ax.scatter(x=PCA_words_embeddings[:, 0],
                  y=PCA_words_embeddings[:, 1],
                  alpha=0.4,
                  cmap='seismic',
                  vmin=-7,
                  vmax=8,
                  c=np.log2(500 * corpus_doc_freq_ingred + 1),
                 )
ScalMappable = cm.ScalarMappable(norm=Normalize(vmin=-7, vmax=8, clip=True), cmap = 'seismic')
cb = fig.colorbar(ScalMappable, ax=ax)
fig.axes[1].set_ylabel('Score absolu ingrédients', fontsize=12)
fig.axes[0].set_xlabel('Coordonnée 1 de la PCA', fontsize=12)
fig.axes[0].set_ylabel('Coordonnée 2 de la PCA', fontsize=12)
fig.suptitle('Scores absolus des embeddings Word2Vec\ndes mots projetés sur leur PCA', fontsize=14)
fig.savefig(Path('..') / 'img' / 'word2vec_PCA.png', bbox_inches='tight')
```



[305]:

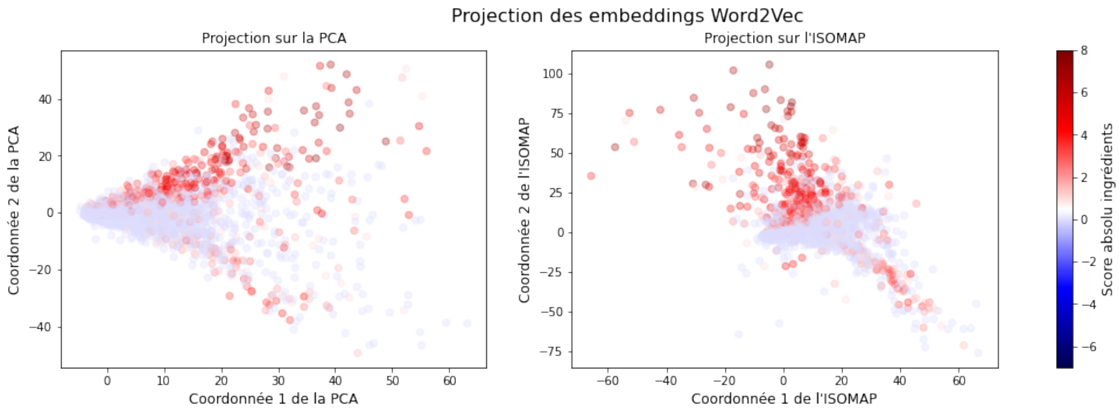
```
mmin, mmax, resolution = -12, 4, 1000
divnorm = colors.TwoSlopeNorm(vmin=mmin, vcenter=0, vmax=mmax)

fig, ax = plt.subplots(figsize=(8, 5))
scat = ax.scatter(x=PCA_words_embeddings[:, 0],
                  y=PCA_words_embeddings[:, 1],
                  alpha=0.2,
                  cmap='seismic',
                  norm=divnorm,
                  c=relative_scores,
                 )
ScalMappable = cm.ScalarMappable(norm=divnorm, cmap = 'seismic')
cb = fig.colorbar(ScalMappable, ax=ax)
fig.axes[1].set_ylabel('Score relatif', fontsize=12)
fig.axes[0].set_xlabel('Coordonnée 1 de la PCA', fontsize=12)
fig.axes[0].set_ylabel('Coordonnée 2 de la PCA', fontsize=12)
fig.suptitle('Scores relatifs des Word2Vec des mots projetés sur leur PCA', fontsize=14)
fig.savefig(Path('..') / 'img' / 'word2vec_PCA_relative.png', bbox_inches='tight')
```



[275]:
```
isomap_model = Isomap(n_neighbors=5, n_components=2, n_jobs=8)
isomap_words_embeddings = isomap_model.fit_transform(scaled_words_embeddings)
print(isomap_words_embeddings.shape)
```

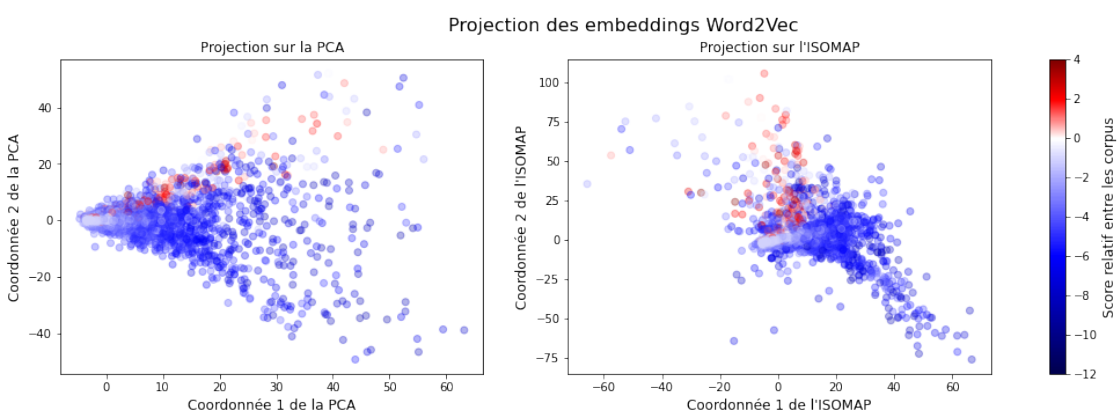
(15465, 2)

[309]:
```
fig, axs = plt.subplots(ncols=2, figsize=(18, 5))
scat = axs[0].scatter(x=PCA_words_embeddings[:, 0],
                      y=PCA_words_embeddings[:, 1],
                      alpha=0.3,
                      cmap='seismic',
                      vmin=-7,
                      vmax=8,
                      c=np.log2(500 * corpus_doc_freq_ingred + 1),
                     )
scat = axs[1].scatter(x=isomap_words_embeddings[:, 0],
                      y=isomap_words_embeddings[:, 1],
                      alpha=0.3,
                      cmap='seismic',
                      vmin=-7,
                      vmax=8,
                      c=np.log2(500 * corpus_doc_freq_ingred + 1),
                     )
ScalMappable = cm.ScalarMappable(norm=Normalize(vmin=-7, vmax=8, clip=True), cmap = 'seismic')
cb = fig.colorbar(ScalMappable, ax=axs)
fig.axes[2].set_ylabel("Score absolu ingrédients", fontsize=12)
fig.axes[0].set_xlabel("Coordonnée 1 de la PCA", fontsize=12)
fig.axes[0].set_ylabel("Coordonnée 2 de la PCA", fontsize=12)
fig.axes[0].set_title("Projection sur la PCA", fontsize=12)
fig.axes[1].set_xlabel("Coordonnée 1 de l'ISOMAP", fontsize=12)
fig.axes[1].set_ylabel("Coordonnée 2 de l'ISOMAP", fontsize=12)
fig.axes[1].set_title("Projection sur l'ISOMAP", fontsize=12)
fig.suptitle("Projection des embeddings Word2Vec", fontsize=16)
# fig.savefig(Path('..') / 'img' / 'word2vec_projection.png', bbox_inches='tight')
```



[310]:

```python
mmin, mmax, resolution = -12, 4, 1000
divnorm = colors.TwoSlopeNorm(vmin=mmin, vcenter=0, vmax=mmax)

fig, axs = plt.subplots(ncols=2, figsize=(18, 5))
scat = axs[0].scatter(x=PCA_words_embeddings[:, 0],
                      y=PCA_words_embeddings[:, 1],
                      alpha=0.3,
                      cmap='seismic',
                      norm=divnorm,
                      c=relative_scores,
                     )
scat = axs[1].scatter(x=isomap_words_embeddings[:, 0],
                      y=isomap_words_embeddings[:, 1],
                      alpha=0.3,
                      cmap='seismic',
                      norm=divnorm,
                      c=relative_scores,
                     )
ScalMappable = cm.ScalarMappable(norm=divnorm, cmap = 'seismic')
cb = fig.colorbar(ScalMappable, ax=axs)
fig.axes[2].set_ylabel("Score relatif entre les corpus", fontsize=12)
fig.axes[0].set_xlabel("Coordonnée 1 de la PCA", fontsize=12)
fig.axes[0].set_ylabel("Coordonnée 2 de la PCA", fontsize=12)
fig.axes[0].set_title("Projection sur la PCA", fontsize=12)
fig.axes[1].set_xlabel("Coordonnée 1 de l'ISOMAP", fontsize=12)
fig.axes[1].set_ylabel("Coordonnée 2 de l'ISOMAP", fontsize=12)
fig.axes[1].set_title("Projection sur l'ISOMAP", fontsize=12)
fig.suptitle("Projection des embeddings Word2Vec", fontsize=16)
# fig.savefig(Path('..') / 'img' / 'word2vec_projection_relative.png', bbox_inches='tight')
```



4.3 Représentations des textes

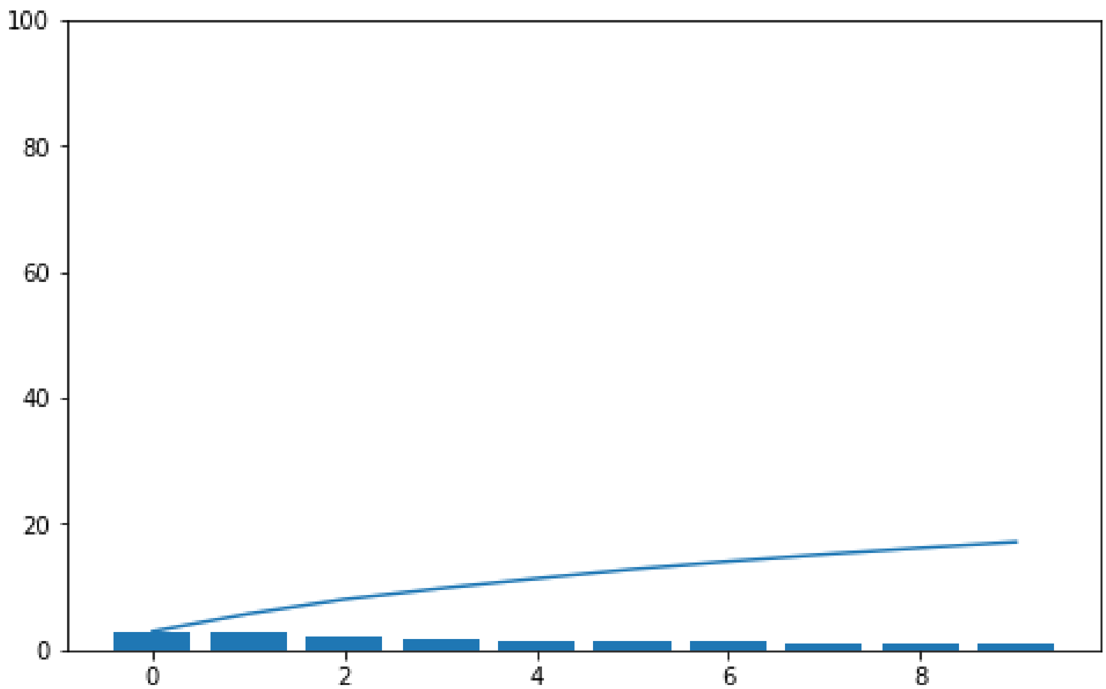
4.3.1 Bag of Words : comptes

Je fais une PCA sur les vecteurs de comptes. Mais d'abord, il faut standardiser.

[320]:
```
vectorized_std = StandardScaler().fit_transform(np.array(vectorized_corpus.todense()))
PCA_model = PCA(n_components=10)
decomp = PCA_model.fit_transform(vectorized_std)
```

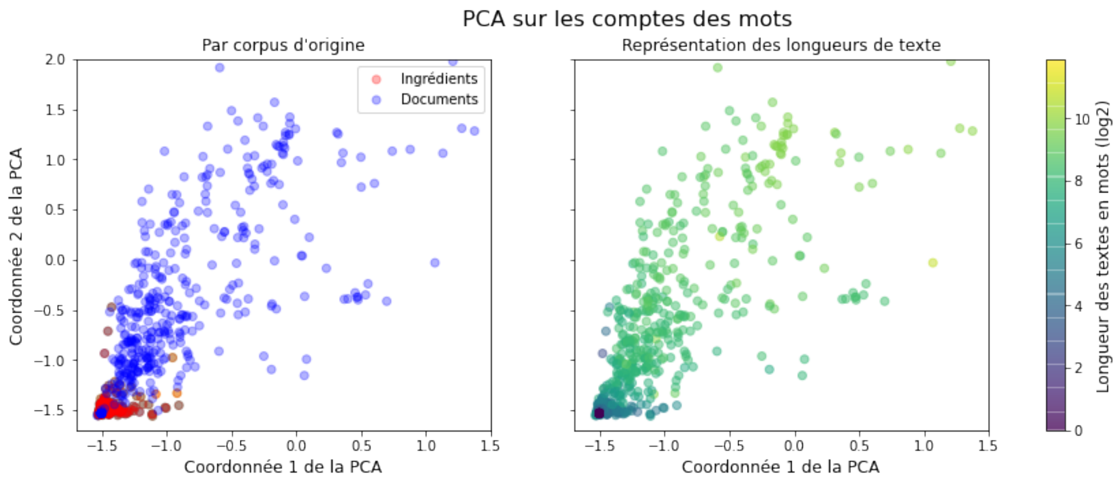
[321]:
```
fig, ax = plt.subplots(figsize=(8, 5))
ax.plot(PCA_model.explained_variance_ratio_.cumsum()*100)
ax.bar(x=range(10), height=PCA_model.explained_variance_ratio_*100)
ax.set_ylim(0, 100)
```

[321]: (0.0, 100.0)



[322]:
```
fig, ax = plt.subplots(ncols=2, figsize=(15, 5), sharey=True)
handles = []

ax[0].scatter(x=decomp[:500, 0],
              y=decomp[:500, 1],
              c=np.log2(np.array(vectorized_corpus[:500,:].sum(axis=1)).flatten() + 1),
              cmap='viridis',
              alpha=0.5)

handles.append(ax[0].scatter(x=decomp[:500, 0],
                             y=decomp[:500, 1],
                             c=['red']*500,
                             alpha=0.3))
handles.append(ax[0].scatter(x=decomp[500:, 0],
                             y=decomp[500:, 1],
                             c=['blue']*500,
                             alpha=0.3))

handles.append(ax[1].scatter(x=decomp[:, 0],
                             y=decomp[:, 1],
                             c=np.log2(np.array(vectorized_corpus[:,:].sum(axis=1)).flatten() + 1),
                             cmap='viridis',
                             alpha=0.5))
```

```python
ax[0].set_xlim(-1.7, 1.5)
ax[0].set_ylim(-1.7, 2)
ax[1].set_xlim(-1.7, 1.5)
ax[1].set_ylim(-1.7, 2)
ax[0].legend(handles[:-1], ['Ingrédients', 'Documents'])
cb = fig.colorbar(handles[-1], ax=ax)
fig.axes[2].set_ylabel("Longueur des textes en mots (log2)", fontsize=12)
fig.suptitle("PCA sur les comptes des mots", fontsize=16)
ax[0].set_ylabel("Coordonnée 2 de la PCA", fontsize=12)
ax[0].set_xlabel("Coordonnée 1 de la PCA", fontsize=12)
ax[0].set_title("Par corpus d'origine", fontsize=12)
ax[1].set_xlabel("Coordonnée 1 de la PCA", fontsize=12)
ax[1].set_title("Représentation des longueurs de texte", fontsize=12)
# fig.savefig(Path('..') / 'img' / 'PCA_counts.png', bbox_inches='tight')
```



4.3.2 tSVD

Je commence par faire un tSVD sur le corpus, en différenciant les ingrédients du texte des fiches techniques. Dans ce premier cas, on a les comptes des mots dans la vectorisation.

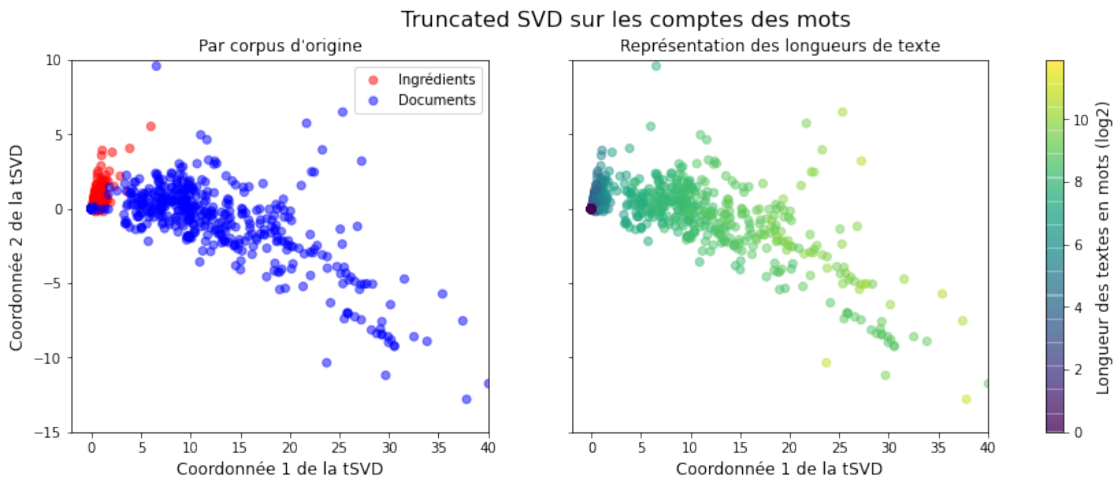
[323]:
```python
vectorized_corpus.todense()
```

[323]:
```
matrix([[ 0.,  0.,  0., …,  0.,  0.,  0.],
        [ 0.,  0.,  0., …,  0.,  0.,  0.],
        [ 0.,  0.,  0., …,  0.,  0.,  0.],
        …,
        [ 1.,  0.,  0., …,  0.,  0.,  0.],
        [ 2.,  1.,  0., …,  0.,  0.,  0.],
        [11.,  0.,  0., …,  0.,  0.,  0.]])
```

[324]:
```python
transformer = TruncatedSVD(n_components=100)
projected = transformer.fit_transform(vectorized_corpus)
```

[325]:
```python
fig, ax = plt.subplots(ncols=2, figsize=(15, 5), sharey=True)
handles = []
handles.append(ax[0].scatter(x=projected[:500, 0], y=projected[:500, 1], c=['red']*500, alpha=0.5))
handles.append(ax[0].scatter(x=projected[500:, 0], y=projected[500:, 1], c=['blue']*500, alpha=0.5))
handles.append(ax[1].scatter(x=projected[:, 0],
                             y=projected[:, 1],
                             c=np.log2(np.array(vectorized_corpus[:,:].sum(axis=1)).flatten() + 1),
                             cmap='viridis',
                             alpha=0.5))
ax[0].set_ylim(-15, 10)
ax[0].set_xlim(-2, 40)
ax[1].set_ylim(-15, 10)
ax[1].set_xlim(-2, 40)
ax[0].legend(handles[:-1], ['Ingrédients', 'Documents'])
cb = fig.colorbar(handles[-1], ax=ax)
fig.axes[2].set_ylabel("Longueur des textes en mots (log2)", fontsize=12)
fig.suptitle("Truncated SVD sur les comptes des mots", fontsize=16)
```

```python
ax[0].set_ylabel("Coordonnée 2 de la tSVD", fontsize=12)
ax[0].set_xlabel("Coordonnée 1 de la tSVD", fontsize=12)
ax[0].set_title("Par corpus d'origine", fontsize=12)
ax[1].set_xlabel("Coordonnée 1 de la tSVD", fontsize=12)
ax[1].set_title("Représentation des longueurs de texte", fontsize=12)
# fig.savefig(Path('..') / 'img' / 'tSVD_counts.png', bbox_inches='tight')
```



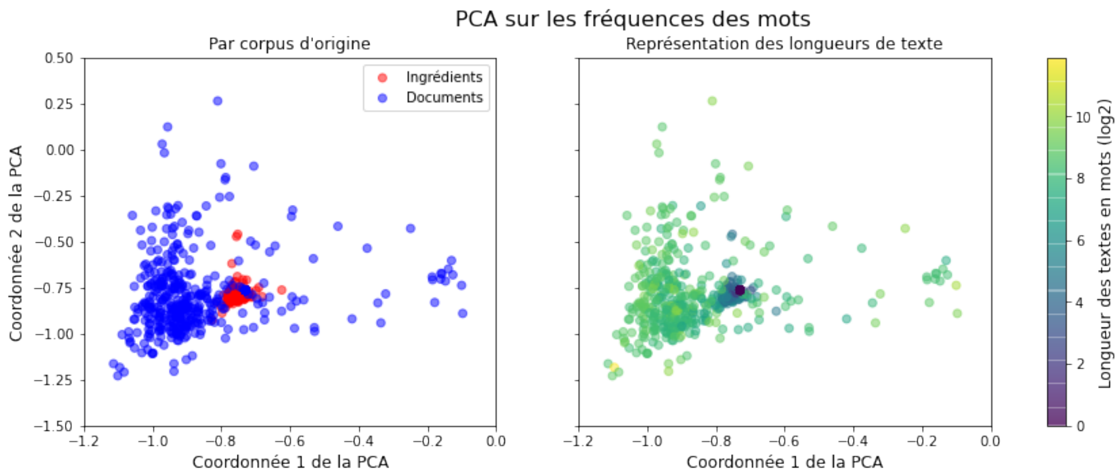
4.3.3 PCA : fréquences

En utilisant cette fois la term frequency. PCA

[326]:
```python
tf_corpus_model = clone(tfidf_corpus)
tf_corpus = tf_corpus_model.set_params(norm='l1').fit_transform(corpus_df.loc[:, 'text'])
```

[327]:
```python
vectorized_std = StandardScaler().fit_transform(np.array(tf_corpus.todense()))
decomp = PCA(n_components=10).fit_transform(vectorized_std)
```

[332]:
```python
fig, ax = plt.subplots(ncols=2, figsize=(15, 5), sharey=True)
handles = []
handles.append(ax[0].scatter(x=decomp[:500, 0], y=decomp[:500, 1], c=['red']*500, alpha=0.5))
handles.append(ax[0].scatter(x=decomp[500:, 0], y=decomp[500:, 1], c=['blue']*500, alpha=0.5))
handles.append(ax[1].scatter(x=decomp[:, 0],
                             y=decomp[:, 1],
                             c=np.log2(np.array(vectorized_corpus[:,:].sum(axis=1)).flatten() + 1),
                             alpha=0.5,
                             cmap='viridis'))
ax[0].set_xlim(-1.2, 0)
ax[0].set_ylim(-1.5, 0.5)
ax[1].set_xlim(-1.2, 0)
ax[1].set_ylim(-1.5, 0.5)
ax[0].legend(handles[:-1], ['Ingrédients', 'Documents'])
cb = fig.colorbar(handles[-1], ax=ax)
fig.axes[2].set_ylabel("Longueur des textes en mots (log2)", fontsize=12)
fig.suptitle("PCA sur les fréquences des mots", fontsize=16)
ax[0].set_ylabel("Coordonnée 2 de la PCA", fontsize=12)
ax[0].set_xlabel("Coordonnée 1 de la PCA", fontsize=12)
ax[0].set_title("Par corpus d'origine", fontsize=12)
ax[1].set_xlabel("Coordonnée 1 de la PCA", fontsize=12)
ax[1].set_title("Représentation des longueurs de texte", fontsize=12)
fig.savefig(Path('..') / 'img' / 'PCA_freq.png', bbox_inches='tight')
```

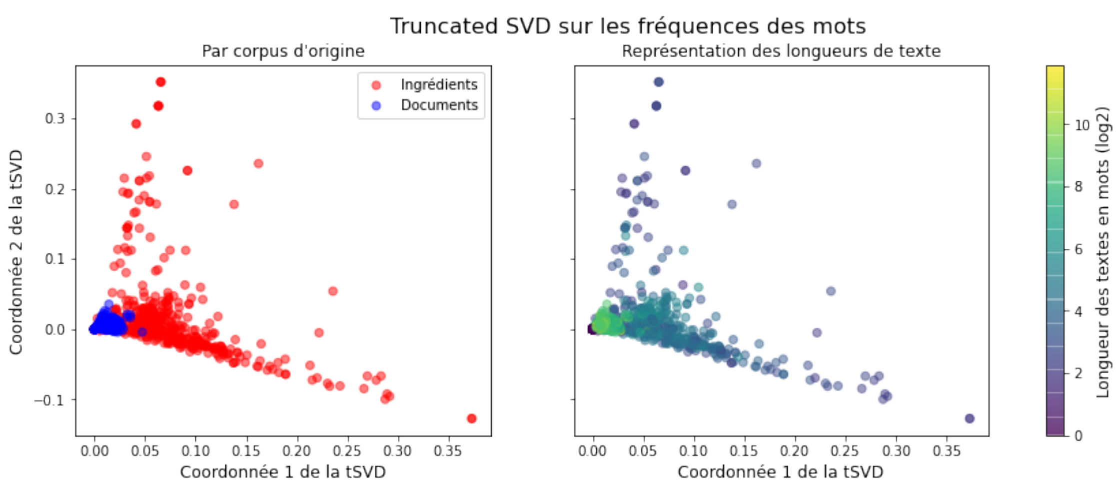


4.3.4 tSVD : fréquences

Voila.

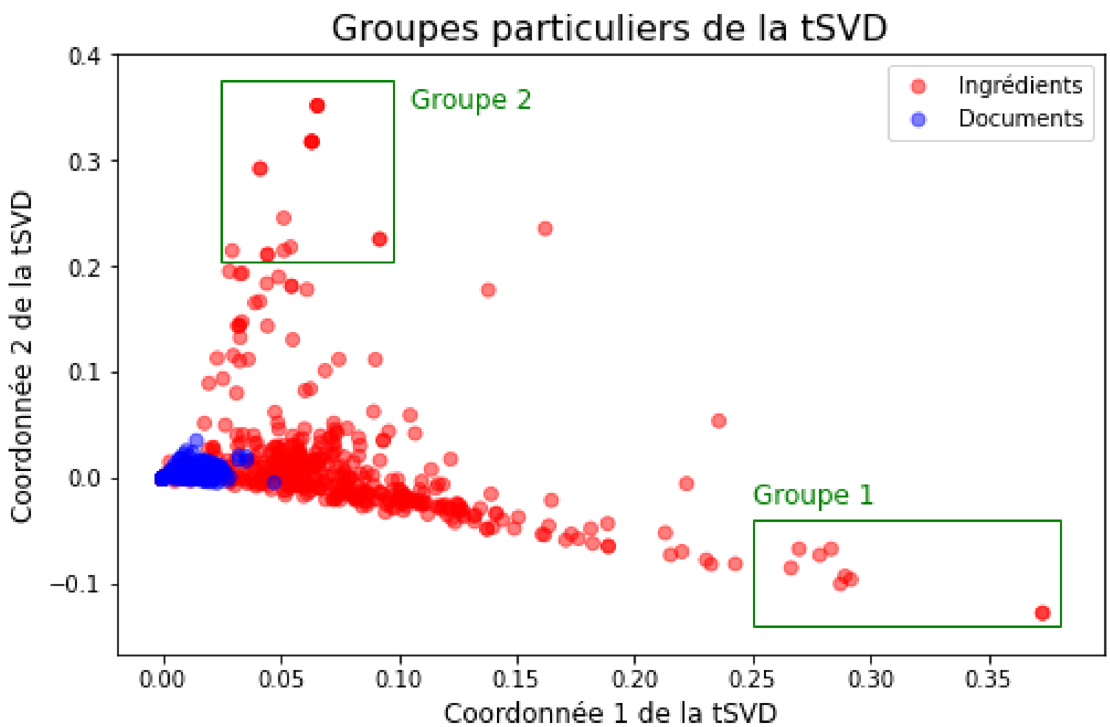
[329]:
```
transformer = TruncatedSVD(n_components=100)
projected = transformer.fit_transform(tf_corpus)
```

[330]:
```
fig, ax = plt.subplots(ncols=2, figsize=(15, 5), sharey=True)
handles = []
handles.append(ax[0].scatter(x=projected[:500, 0], y=projected[:500, 1], c=['red']*500, alpha=0.5))
handles.append(ax[0].scatter(x=projected[500:, 0], y=projected[500:, 1], c=['blue']*500, alpha=0.5))
handles.append(ax[1].scatter(x=projected[:, 0],
                             y=projected[:, 1],
                             c=np.log2(np.array(vectorized_corpus[:,:].sum(axis=1)).flatten() + 1),
                             alpha=0.5,
                             cmap='viridis'))
# ax.set_ylim(-15, 10)
# ax.set_xlim(-2, 40)
ax[0].legend(handles, ['Ingrédients', 'Documents'])
cb = fig.colorbar(handles[-1], ax=ax)
fig.axes[2].set_ylabel("Longueur des textes en mots (log2)", fontsize=12)
fig.suptitle("Truncated SVD sur les fréquences des mots", fontsize=16)
ax[0].set_ylabel("Coordonnée 2 de la tSVD", fontsize=12)
ax[0].set_xlabel("Coordonnée 1 de la tSVD", fontsize=12)
ax[0].set_title("Par corpus d'origine", fontsize=12)
ax[1].set_xlabel("Coordonnée 1 de la tSVD", fontsize=12)
ax[1].set_title("Représentation des longueurs de texte", fontsize=12)
# fig.savefig(Path('..') / 'img' / 'tSVD_freq.png', bbox_inches='tight')
```



[433]:

```
fig, ax = plt.subplots(figsize=(8, 5))
handles = []
handles.append(ax.scatter(x=projected[:500, 0], y=projected[:500, 1], c=['red']*500, alpha=0.5))
handles.append(ax.scatter(x=projected[500:, 0], y=projected[500:, 1], c=['blue']*500, alpha=0.5))
ax.add_patch(mpatch.Rectangle((0.25, -0.14), 0.13, 0.1, fill=False, color='green'))
ax.add_patch(mpatch.Rectangle((0.025, 0.205), 0.073, 0.17, fill=False, color='green'))
ax.annotate('Groupe 1', (0.25, -0.025), fontsize=12, color='green')
ax.annotate('Groupe 2', (0.105, 0.35), fontsize=12, color='green')
ax.legend(handles, ['Ingrédients', 'Documents'])
ax.set_ylabel("Coordonnée 2 de la tSVD", fontsize=12)
ax.set_xlabel("Coordonnée 1 de la tSVD", fontsize=12)
ax.set_title("Groupes particuliers de la tSVD", fontsize=16)
# fig.savefig(Path('..') / 'img' / 'tSVD_freq_groups.png', bbox_inches='tight')
```



[434]:

```
sample = pd.concat([corpus_df.reset_index(), pd.DataFrame(projected[:, [0, 1]], columns=['x', 'y'])], axis=1)
```

[435]:

```
idx1 = ((projected[:, 0] > 0.25) &
        (projected[:, 0] < (0.25+0.13)) &
        (projected[:, 1] < (-0.14+0.1)) &
        (projected[:, 1] > -0.14))
idx2 = ((projected[:, 0] > 0.025) &
        (projected[:, 0] < (0.025+0.073)) &
        (projected[:, 1] < (0.205+0.17)) &
        (projected[:, 1] > 0.205))

sample.loc[idx1, 'group'] = 'Groupe 1'
sample.loc[idx2, 'group'] = 'Groupe 2'
with pd.option_context("max_colwidth", 100000):
    tex_str = (sample.loc[idx1 | idx2]
                     .set_index('group')
                     .sort_index()
                     .loc[:, ['text', 'x', 'y']]
                     .rename({'text': 'Texte'}, axis=1)
                     .to_latex(multirow=True,
                               column_format='llcc',
                               index_names=False,
                              )
```

```python
                    .replace(r'\textbackslash n', r' \newline '))
    print(tex_str)
# with open(Path('..') / 'tbls' / 'tSVD_sample.tex', mode='w') as file:
#     file.write(tex_str)
```

```
\begin{tabular}{llcc}
\toprule
{} &                                                             Texte &         x &         y \\
\midrule
Groupe 1 &                                                    Thon, eau, sel &  0.373079 & -0.127052 \\
Groupe 1 &                                         Pois chiches, eau, sel. &  0.266423 & -0.084501 \\
Groupe 1 &                                        Haricots beurre, eau, sel &  0.283409 & -0.066561 \\
Groupe 1 &                                       Câpres, eau, vinaigre, sel &  0.291819 & -0.095479 \\
Groupe 1 &                                          Thon albacore, eau, sel &  0.287423 & -0.099627 \\
Groupe 1 &                                        Eau, haricots verts, sel. &  0.278588 & -0.072474 \\
Groupe 1 &                                       Pommes de terre, eau, sel. &  0.289291 & -0.092162 \\
Groupe 1 &                              Carottes rondelles, eau, sel, sucre &  0.269849 & -0.066600 \\
Groupe 1 &                                                    Thon, eau, sel &  0.373079 & -0.127052 \\
Groupe 2 &                     - 100\% Semoule de blé dur de qualité supérieure &  0.065551 &  0.351800 \\
Groupe 2 &                                            100\% haricots blancs &  0.051373 &  0.214921 \\
Groupe 2 &                       100\% Semoule de blé dur de qualité supérieure &  0.065551 &  0.351800 \\
Groupe 2 &              Semoule de blé dur* \newline *issu de l'agriculture biologique &  0.054211 &
0.218192 \\
Groupe 2 &                                                 Tilleul (100\%). &  0.041323 &  0.292199 \\
Groupe 2 &                       100\% semoule de blé dur de qualité supérieure &  0.065551 &  0.351800 \\
Groupe 2 &                                                 Farine de blé T45 &  0.092002 &  0.225689 \\
Groupe 2 &        - Semoule de blé dur de qualité supérieure \newline - 30\% oeufs frais &  0.044446 &
0.211188 \\
Groupe 2 &  - 100\% Semoule de blé dur de qualité courante \newline - Contient du gluten &  0.051337 &
0.245649 \\
Groupe 2 &                            SEMOULE DE BLE' DUR de qualité supérieure &  0.063201 &  0.317653 \\
Groupe 2 &                                                      100\% Arabica &  0.041324 &  0.292222 \\
Groupe 2 &                                                    agar-agar 100\% &  0.029466 &  0.214845 \\
Groupe 2 &                            SEMOULE DE BLE' DUR de qualité supérieure &  0.063201 &  0.317653 \\
Groupe 2 &                            SEMOULE DE BLE' DUR de qualité supérieure &  0.063201 &  0.317653 \\
Groupe 2 &                            SEMOULE DE BLE' DUR de qualité supérieure &  0.063201 &  0.317653 \\
Groupe 2 &        - Semoule de blé dur de qualité supérieure \newline - 30\% oeufs frais &  0.044446 &
0.211188 \\
Groupe 2 &                                                 Farine de blé T45 &  0.092002 &  0.225689 \\
\bottomrule
\end{tabular}
```

[ ]: