1 Tuning du modèle

L'objet de ce notebook est d'illustrer les différentes étapes de tuning du modèle.

1.1 Préambule

1.1.1 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)
```

[2]:
```
# imports and customization of diplay
# import os
import re
from functools import partial
from itertools import product
import numpy as np
import pandas as pd
pd.options.display.min_rows = 6
pd.options.display.width=108
# from sklearn.feature_extraction.text import CountVectorizer
from sklearn.model_selection import train_test_split
# from sklearn.model_selection import cross_val_score, cross_validate
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import FunctionTransformer
from matplotlib import pyplot as plt
import matplotlib.patches as mpatch
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
```

[3]:
```
# monkeypatch _repr_latex_ for better inclusion of dataframes output in report
def _repr_latex_(self, size='scriptsize',):
    return(f"\\resizebox{{\\linewidth}}{{!}}{{\\begin{{{size}}}\\centering{{{self.
↪to_latex()}}}\\end{{{size}}}}}")
pd.DataFrame._repr_latex_ = _repr_latex_
```

1.1.2 Acquisition des données

On récupère les données manuellement étiquetées et on les intègre dans un dataframe

[5]:
```
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.sample(3)
```

```
[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=  35.9s
```

[5]:

	designation	ingredients	path	content	text
uid					
a96191ad-ff50-4182-b4d1-29f1220d92a1	Café chicoré soluble en sachet 500 g SAGY	Mélange soluble composé de 60% de pur café sol...	../../ground_truth/a96191ad-ff50-4182-b4d1-29f...	b'%PDF-1.5\r\n%\xb5\xb5\xb5\xb5\r\n1 0 obj\r\n...	1 326 kJ / 315 kcal\n\n0,30 g\n\n< 0,20 g\n\n5...
9fa94fea-6315-4439-b976-0730d37522c9	Chapelure Batter Mix en sac de 4,2 kg GRIFFITH...		../../ground_truth/9fa94fea-6315-4439-b976-073...	b'%PDF-1.5\r\n%\xb5\xb5\xb5\xb5\r\n1 0 obj\r\n...	\n\n \n\nSPECIFICATION PRODUIT \n\n \n\nCODE ...
b29b153c-7244-4bdd-8d36-b5292dcd474b	Compote de pomme allégée en boîte 5/1 EPISAVEURS		../../ground_truth/b29b153c-7244-4bdd-8d36-b52...	b'%PDF-1.4\r\n%\xe2\xe3\xcf\xd3\r\n1 0 obj\r\n...	

1.1.3 Train / Test split

On va appliquer une grid search pour déterminer les meilleurs paramètres de notre modèle. Pour ne pas surestimer la performance du modèle, il est nécessaire de bien séparer le jeu de test du jeu d'entraînement, y compris pour la grid search !

[6]:
```
train, test = train_test_split(texts_df, test_size=100, random_state=42)
```

Dans toute la suite, on utilisera le jeu d'entraînement pour effectuer le tuning des hyperparamètres.

1.2 Ajustement de la fonction de découpage des textes

L'objectif de cette partie est d'optimiser la fonction de découpage des textes en blocs. On va tester quelques fonctions candidates, via une GridSearch.

1.2.1 Définition des fonctions candidates

On définit les fonctions de split :

[7]:
```
# definitions of splitter funcs
splitter_funcs = []
def split_func1(text):
    return(text.split('\n\n'))
splitter_funcs.append(split_func1)
def split_func2(text):
    return(text.split('\n'))
splitter_funcs.append(split_func2)
def split_func3(text):
    regex = r'\s*\n\s*\n\s*'
    return(re.split(regex, text))
splitter_funcs.append(split_func3)
```

1.2.2 Mise en place du pipeline

On construit ensuite un pipeline de traitement du texte. Le SimilaritySelector prenant en entrée une pandas.Series, on définit entre le BlockSplitter (dont la méthode transform() retourne un pandas.DataFrame) et le SimilaritySelector une fonction utilitaire qui séléctionne la colonne `blocks'.

[8]:
```
def select_col(df, col_name='blocks'):
        return(df[col_name].fillna(''))
col_selector = FunctionTransformer(select_col)
```

[9]:
```
process_pipe = Pipeline([('Splitter', BlockSplitter()),
                         ('ColumnSelector', col_selector),
                         ('SimilaritySelector', SimilaritySelector())
                        ],
                        verbose=False)
```

On peut tester le fonctionnement de ce Pipeline. Attention, les résultats ne sont pas représentatifs, on entraîne et on prédit sur le même jeu de données !

[10]:
```
process_pipe.fit(train, train['ingredients'])
process_pipe.predict(train).sample(4)
```

```
Launching 8 processes.
Launching 8 processes.
```

[10]:
```
uid
5cb7f05a-3b2c-440e-af0d-01843fb38cbf    INGRÉDIENTS : Sucre, Gomme base, Sirop de gluc…
7e5ff57f-5a13-46bf-bb1c-b59b40727515                          MORCEAUX DE THON AU NATUREL
8266604c-1ea2-47ca-a4fa-649b4147e733

7528ded6-bec2-418a-b0be-5d06387b2f88    Arômes et couleurs plus ou moins prononcés sui…
dtype: object
```

1.2.3 Helper fonction

On doit faire varier dans la grid search des paramètres qui sont packés sous forme de dictionnaires avant d'être passés au SimilaritySelector. On construit une fonction qui permet de construire le produit cartésien qui va bien pour ces paramètres.

[11]:
```
def prod_params(dict_to_prod):
    """
    In : dict of dicts.
    First level key : parameter name
    Second level key : name of scenario with this parameter value
    Values : parameter value

    Returns a tuple:
        - list of labels to name scenario
        - list of dictionaries to pass to count_vect_kwargs
    """
    label_lists = [list(dict_.keys()) for dict_ in dict_to_prod.values()]
    labels = list(map(lambda x: ', '.join(x), list(product(*label_lists))))
    values_iter = list(product(*[list(dict_.values()) for dict_ in dict_to_prod.values()]))
    parms_names = list(dict_to_prod.keys())
    dict_out = [{key: val for (key, val) in zip(parms_names, values_)} for values_ in values_iter]
    return(labels, dict_out)
```

[12]:
```
prod_params({'stop_words': {'no stopwords removal': None, 'with stopwords removal' : {'de', 'le'}},
             'ngram_ranges': {'no_ngram': (1, 1), 'bigrams': (1, 2)}})
```

[12]:
```
(['no stopwords removal, no_ngram',
  'no stopwords removal, bigrams',
  'with stopwords removal, no_ngram',
  'with stopwords removal, bigrams'],
 [{'stop_words': None, 'ngram_ranges': (1, 1)},
  {'stop_words': None, 'ngram_ranges': (1, 2)},
  {'stop_words': {'de', 'le'}, 'ngram_ranges': (1, 1)},
  {'stop_words': {'de', 'le'}, 'ngram_ranges': (1, 2)}])
```

1.2.4 Stockage des résultats dans un dataframe

Au fil des lancements des grid search, on stockera les données dans un dataframe afin de pouvoir les analyser plus simplement après coup.

[14]:
```
result_df = pd.DataFrame()
```

1.2.5 Application de la GridSearch : tuning du text preprocessing (run 1)

On applique ensuite une grid search en faisant varier les fonctions de text preprocessing : - fonction de split du texte des documents en blocs - retrait ou non de stopwords - prise en compte de ngrams - juste pour une première comparaison, choix du candidat par projection l1/l2 ou par similarité cosinus

On scorera via la similarité de Levenshtein.

[15]:
```
lev_scorer = partial(text_sim_score, similarity='levenshtein')
```

[16]:
```
stop_words = {'pas', 'le', 'en', 'pour', 'ou', 'ce', 'de', 'dans', 'du', 'and', 'un', 'sur', 'et',
              'of', 'est', 'par', 'la', 'les', 'dont', 'au', 'des', 'que'}
```

[17]:
```
ngram_ranges = {'no_ngram': (1, 1), 'bigrams': (1, 2), 'trigrams': (1, 3)}
```

[18]:
```
kwargs_to_prod = prod_params({'stop_words': {'no stopwords removal': None, 'with stopwords removal' :␣
↪stop_words},
                              'ngram_range': ngram_ranges,
                              'strip_accents': {'keep accents': None, 'remove accents': 'unicode'}
                             }
                            )
```

[19]:
```
param_grid = [{'Splitter__splitter_func': splitter_funcs,
               'SimilaritySelector__similarity': ['projection', 'cosine'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              }
             ]
search = GridSearchCV(process_pipe,
                      param_grid,
                      cv=8,
                      scoring= ({'similarity': lev_scorer, 'accuracy': custom_accuracy}),
                      refit='similarity',
                      n_jobs=-1,
                      verbose=1,
                     ).fit(train, train['ingredients'])
```

```
Fitting 8 folds for each of 72 candidates, totalling 576 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   13.4s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:  1.2min
[Parallel(n_jobs=-1)]: Done 434 tasks      | elapsed:  2.9min

Launching 8 processes.

[Parallel(n_jobs=-1)]: Done 576 out of 576 | elapsed:  3.9min finished
```

[20]:
```
labels = list(product(kwargs_to_prod[0], ['Projection l2/l1', 'Cosinus'], ['Split 1', 'Split 2', 'Split␣
↪3']))
labels = list(map(lambda x: ', '.join(x), labels))
```

[21]:
```
for i in range(len(search.cv_results_['rank_test_similarity'])):
    str_result = f"{search.cv_results_['mean_test_similarity'][i]:.2%} +/- {search.
↪cv_results_['std_test_similarity'][i]:.2%}"
    print(labels[i], str_result)
```

```
no stopwords removal, no_ngram, keep accents, Projection l2/l1, Split 1 50.15% +/- 5.61%
no stopwords removal, no_ngram, keep accents, Projection l2/l1, Split 2 38.90% +/- 4.52%
no stopwords removal, no_ngram, keep accents, Projection l2/l1, Split 3 52.65% +/- 6.09%
no stopwords removal, no_ngram, keep accents, Cosinus, Split 1 40.30% +/- 4.91%
no stopwords removal, no_ngram, keep accents, Cosinus, Split 2 25.87% +/- 2.25%
no stopwords removal, no_ngram, keep accents, Cosinus, Split 3 41.98% +/- 5.27%
no stopwords removal, no_ngram, remove accents, Projection l2/l1, Split 1 49.47% +/- 5.77%
no stopwords removal, no_ngram, remove accents, Projection l2/l1, Split 2 38.56% +/- 4.19%
no stopwords removal, no_ngram, remove accents, Projection l2/l1, Split 3 52.02% +/- 6.05%
no stopwords removal, no_ngram, remove accents, Cosinus, Split 1 40.93% +/- 5.02%
no stopwords removal, no_ngram, remove accents, Cosinus, Split 2 26.06% +/- 2.00%
no stopwords removal, no_ngram, remove accents, Cosinus, Split 3 42.68% +/- 5.42%
no stopwords removal, bigrams, keep accents, Projection l2/l1, Split 1 55.47% +/- 5.22%
no stopwords removal, bigrams, keep accents, Projection l2/l1, Split 2 43.12% +/- 2.32%
no stopwords removal, bigrams, keep accents, Projection l2/l1, Split 3 58.38% +/- 5.06%
no stopwords removal, bigrams, keep accents, Cosinus, Split 1 41.53% +/- 5.73%
```

```
no stopwords removal, bigrams, keep accents, Cosinus, Split 2 26.94% +/- 2.14%
no stopwords removal, bigrams, keep accents, Cosinus, Split 3 43.45% +/- 6.40%
no stopwords removal, bigrams, remove accents, Projection l2/l1, Split 1 55.40% +/- 5.11%
no stopwords removal, bigrams, remove accents, Projection l2/l1, Split 2 43.27% +/- 2.78%
no stopwords removal, bigrams, remove accents, Projection l2/l1, Split 3 58.31% +/- 5.23%
no stopwords removal, bigrams, remove accents, Cosinus, Split 1 41.49% +/- 5.88%
no stopwords removal, bigrams, remove accents, Cosinus, Split 2 27.27% +/- 1.95%
no stopwords removal, bigrams, remove accents, Cosinus, Split 3 43.70% +/- 6.48%
no stopwords removal, trigrams, keep accents, Projection l2/l1, Split 1 56.41% +/- 5.05%
no stopwords removal, trigrams, keep accents, Projection l2/l1, Split 2 43.75% +/- 3.06%
no stopwords removal, trigrams, keep accents, Projection l2/l1, Split 3 59.56% +/- 5.12%
no stopwords removal, trigrams, keep accents, Cosinus, Split 1 41.54% +/- 5.25%
no stopwords removal, trigrams, keep accents, Cosinus, Split 2 26.95% +/- 2.41%
no stopwords removal, trigrams, keep accents, Cosinus, Split 3 43.54% +/- 6.16%
no stopwords removal, trigrams, remove accents, Projection l2/l1, Split 1 56.43% +/- 5.07%
no stopwords removal, trigrams, remove accents, Projection l2/l1, Split 2 43.83% +/- 3.11%
no stopwords removal, trigrams, remove accents, Projection l2/l1, Split 3 59.58% +/- 5.11%
no stopwords removal, trigrams, remove accents, Cosinus, Split 1 42.08% +/- 5.14%
no stopwords removal, trigrams, remove accents, Cosinus, Split 2 27.28% +/- 2.39%
no stopwords removal, trigrams, remove accents, Cosinus, Split 3 44.18% +/- 6.17%
with stopwords removal, no_ngram, keep accents, Projection l2/l1, Split 1 54.94% +/- 5.62%
with stopwords removal, no_ngram, keep accents, Projection l2/l1, Split 2 42.12% +/- 4.32%
with stopwords removal, no_ngram, keep accents, Projection l2/l1, Split 3 58.06% +/- 6.52%
with stopwords removal, no_ngram, keep accents, Cosinus, Split 1 51.06% +/- 6.89%
with stopwords removal, no_ngram, keep accents, Cosinus, Split 2 29.73% +/- 4.76%
with stopwords removal, no_ngram, keep accents, Cosinus, Split 3 53.35% +/- 7.12%
with stopwords removal, no_ngram, remove accents, Projection l2/l1, Split 1 54.89% +/- 5.81%
with stopwords removal, no_ngram, remove accents, Projection l2/l1, Split 2 42.22% +/- 4.32%
with stopwords removal, no_ngram, remove accents, Projection l2/l1, Split 3 57.99% +/- 6.66%
with stopwords removal, no_ngram, remove accents, Cosinus, Split 1 51.40% +/- 6.72%
with stopwords removal, no_ngram, remove accents, Cosinus, Split 2 30.44% +/- 4.69%
with stopwords removal, no_ngram, remove accents, Cosinus, Split 3 53.69% +/- 7.13%
with stopwords removal, bigrams, keep accents, Projection l2/l1, Split 1 57.74% +/- 5.74%
with stopwords removal, bigrams, keep accents, Projection l2/l1, Split 2 44.54% +/- 3.57%
with stopwords removal, bigrams, keep accents, Projection l2/l1, Split 3 61.08% +/- 5.91%
with stopwords removal, bigrams, keep accents, Cosinus, Split 1 52.31% +/- 7.10%
with stopwords removal, bigrams, keep accents, Cosinus, Split 2 26.86% +/- 4.47%
with stopwords removal, bigrams, keep accents, Cosinus, Split 3 54.85% +/- 7.51%
with stopwords removal, bigrams, remove accents, Projection l2/l1, Split 1 57.99% +/- 5.69%
with stopwords removal, bigrams, remove accents, Projection l2/l1, Split 2 44.43% +/- 3.30%
with stopwords removal, bigrams, remove accents, Projection l2/l1, Split 3 60.86% +/- 5.65%
with stopwords removal, bigrams, remove accents, Cosinus, Split 1 51.79% +/- 6.83%
with stopwords removal, bigrams, remove accents, Cosinus, Split 2 26.90% +/- 4.71%
with stopwords removal, bigrams, remove accents, Cosinus, Split 3 54.43% +/- 7.18%
with stopwords removal, trigrams, keep accents, Projection l2/l1, Split 1 58.76% +/- 5.47%
with stopwords removal, trigrams, keep accents, Projection l2/l1, Split 2 45.36% +/- 3.58%
with stopwords removal, trigrams, keep accents, Projection l2/l1, Split 3 61.94% +/- 5.59%
with stopwords removal, trigrams, keep accents, Cosinus, Split 1 51.65% +/- 6.90%
with stopwords removal, trigrams, keep accents, Cosinus, Split 2 25.74% +/- 4.50%
with stopwords removal, trigrams, keep accents, Cosinus, Split 3 54.28% +/- 7.24%
with stopwords removal, trigrams, remove accents, Projection l2/l1, Split 1 58.82% +/- 5.48%
with stopwords removal, trigrams, remove accents, Projection l2/l1, Split 2 45.54% +/- 3.61%
with stopwords removal, trigrams, remove accents, Projection l2/l1, Split 3 62.01% +/- 5.61%
with stopwords removal, trigrams, remove accents, Cosinus, Split 1 51.54% +/- 6.74%
with stopwords removal, trigrams, remove accents, Cosinus, Split 2 26.04% +/- 4.42%
with stopwords removal, trigrams, remove accents, Cosinus, Split 3 54.26% +/- 7.21%
```

On tire de ce premier test: - que le modèle est bien plus performant avec le retrait des stopwords - que le split le plus efficace est la fonction qui applique la regex (deux retours chariots parmi des whitespaces) - split 3 - que la prise en compte de bigrammes améliore, avec les trigrammes en plus on ne gagne rien - que la similarité cosinus semble sensiblement moins performante que le choix par projection (l2/l1)

Remarque : la standard dev est quand même assez élevée (de l'ordre de 5-6%). Les scénarios avec peu d'écart entre leurs moyennes (2-3%) ne sont pas départageables via cette grid search.

On sauvegarde les résultat dans le dataframe qu'on analysera à la fin

[22]:
```python
try:
    result_df = result_df.loc[result_df['run'] != 1].copy()
except:
    pass
result_df = pd.DataFrame(search.cv_results_)
result_df['run'] = 1
```

1.2.6 Application de la Grid Search : tuning du calcul de similarité (run 2)

On va maintenant déterminer, sur la base des paramètres déjà retenus, le mode de calcul de similarité le plus performant. Seul le calcul par projection est paramétrique (norme dans l'espace de départ vs. norme sur l'espace projeté), on fera uniquement varier ces paramètres (en plus de la comparaison avec la similarité cosinus).

On comparera également la performance du modèle selon qu'on vectorise les textes via les comptes de mots, ou bien seulement via un identifiant binaire (présence ou absence du mot).

[23]:
```python
process_pipe.set_params(**{'Splitter__splitter_func': splitter_funcs[2],
                           })

kwargs_to_prod = prod_params({'stop_words': {'with stopwords removal' : stop_words},
                              'ngram_range': {'bigrams': (1, 2)},
                              'binary': {'counts': False, 'binary flag': True},
                              'strip_accents': {'remove accents': 'unicode'}
                             })

param_grid = [{
               'SimilaritySelector__source_norm': ['l1'],
               'SimilaritySelector__projected_norm': ['l1'],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__source_norm': ['l2'],
               'SimilaritySelector__projected_norm': ['l2'],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__source_norm': ['l2'],
               'SimilaritySelector__projected_norm': ['l1'],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__source_norm': ['l3'],
               'SimilaritySelector__projected_norm': ['l2'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__source_norm': ['l4'],
               'SimilaritySelector__projected_norm': ['l3'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__source_norm': ['l5'],
               'SimilaritySelector__projected_norm': ['l4'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__source_norm': ['l6'],
               'SimilaritySelector__projected_norm': ['l5'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
```

```
              },
              {
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__source_norm': ['l3'],
               'SimilaritySelector__projected_norm': ['l1'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__source_norm': ['l4'],
               'SimilaritySelector__projected_norm': ['l2'],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__source_norm': ['l5'],
               'SimilaritySelector__projected_norm': ['l3'],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__source_norm': ['l6'],
               'SimilaritySelector__projected_norm': ['l4'],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__source_norm': ['l7'],
               'SimilaritySelector__projected_norm': ['l5'],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__source_norm': ['l4'],
               'SimilaritySelector__projected_norm': ['l1'],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__source_norm': ['l5'],
               'SimilaritySelector__projected_norm': ['l2'],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__source_norm': ['l6'],
               'SimilaritySelector__projected_norm': ['l3'],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__source_norm': ['l7'],
               'SimilaritySelector__projected_norm': ['l4'],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__source_norm': ['l8'],
               'SimilaritySelector__projected_norm': ['l5'],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              },
              {
               'SimilaritySelector__similarity': ['cosine'],
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
              }
             ]
search = GridSearchCV(process_pipe,
```

```
                       param_grid,
                       cv=8,
                       scoring= ({'similarity': lev_scorer, 'accuracy': custom_accuracy}),
                       refit='similarity',
                       n_jobs=-1,
                       verbose=1,
                      ).fit(train, train['ingredients'])
```

```
Fitting 8 folds for each of 36 candidates, totalling 288 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   14.9s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:  1.2min

Launching 8 processes.

[Parallel(n_jobs=-1)]: Done 288 out of 288 | elapsed:  1.8min finished
```

[24]:

```
labels = ['l1, l1',
          'l2, l2',
          'l2, l1',
          'l3, l2',
          'l4, l3',
          'l5, l4',
          'l6, l5',
          'l3, l1',
          'l4, l2',
          'l5, l3',
          'l6, l4',
          'l7, l5',
          'l4, l1',
          'l5, l2',
          'l6, l3',
          'l7, l4',
          'l8, l5',
          'cosine',
         ]

labels = list(product(labels, kwargs_to_prod[0]))
labels = list(map(lambda x: ', '.join(x), labels))

for i in range(len(search.cv_results_['rank_test_similarity'])):
    str_result = f"{search.cv_results_['mean_test_similarity'][i]:.2%} +/- {search.
↪cv_results_['std_test_similarity'][i]:.2%}"
    print(labels[i], str_result)
```

```
l1, l1, with stopwords removal, bigrams, counts, remove accents 17.87% +/- 2.52%
l1, l1, with stopwords removal, bigrams, binary flag, remove accents 17.90% +/- 2.55%
l2, l2, with stopwords removal, bigrams, counts, remove accents 17.87% +/- 2.52%
l2, l2, with stopwords removal, bigrams, binary flag, remove accents 17.90% +/- 2.55%
l2, l1, with stopwords removal, bigrams, counts, remove accents 60.86% +/- 5.65%
l2, l1, with stopwords removal, bigrams, binary flag, remove accents 61.00% +/- 5.61%
l3, l2, with stopwords removal, bigrams, counts, remove accents 61.55% +/- 5.25%
l3, l2, with stopwords removal, bigrams, binary flag, remove accents 62.05% +/- 4.73%
l4, l3, with stopwords removal, bigrams, counts, remove accents 59.61% +/- 4.00%
l4, l3, with stopwords removal, bigrams, binary flag, remove accents 62.61% +/- 4.29%
l5, l4, with stopwords removal, bigrams, counts, remove accents 56.23% +/- 3.40%
l5, l4, with stopwords removal, bigrams, binary flag, remove accents 61.82% +/- 3.67%
l6, l5, with stopwords removal, bigrams, counts, remove accents 51.58% +/- 3.78%
l6, l5, with stopwords removal, bigrams, binary flag, remove accents 60.91% +/- 3.62%
l3, l1, with stopwords removal, bigrams, counts, remove accents 59.33% +/- 5.34%
l3, l1, with stopwords removal, bigrams, binary flag, remove accents 59.06% +/- 5.44%
l4, l2, with stopwords removal, bigrams, counts, remove accents 61.11% +/- 5.30%
l4, l2, with stopwords removal, bigrams, binary flag, remove accents 61.00% +/- 5.61%
l5, l3, with stopwords removal, bigrams, counts, remove accents 59.28% +/- 3.60%
l5, l3, with stopwords removal, bigrams, binary flag, remove accents 61.70% +/- 5.21%
l6, l4, with stopwords removal, bigrams, counts, remove accents 55.73% +/- 4.26%
```

```
l6, l4, with stopwords removal, bigrams, binary flag, remove accents 62.05% +/- 4.73%
l7, l5, with stopwords removal, bigrams, counts, remove accents 50.18% +/- 2.42%
l7, l5, with stopwords removal, bigrams, binary flag, remove accents 61.96% +/- 4.23%
l4, l1, with stopwords removal, bigrams, counts, remove accents 58.42% +/- 5.53%
l4, l1, with stopwords removal, bigrams, binary flag, remove accents 57.44% +/- 5.05%
l5, l2, with stopwords removal, bigrams, counts, remove accents 60.29% +/- 4.59%
l5, l2, with stopwords removal, bigrams, binary flag, remove accents 59.67% +/- 5.18%
l6, l3, with stopwords removal, bigrams, counts, remove accents 58.12% +/- 3.67%
l6, l3, with stopwords removal, bigrams, binary flag, remove accents 61.00% +/- 5.61%
l7, l4, with stopwords removal, bigrams, counts, remove accents 53.31% +/- 2.96%
l7, l4, with stopwords removal, bigrams, binary flag, remove accents 61.50% +/- 5.35%
l8, l5, with stopwords removal, bigrams, counts, remove accents 47.87% +/- 2.99%
l8, l5, with stopwords removal, bigrams, binary flag, remove accents 61.80% +/- 5.20%
cosine, with stopwords removal, bigrams, counts, remove accents 54.43% +/- 7.18%
cosine, with stopwords removal, bigrams, binary flag, remove accents 53.36% +/- 7.86%
```

On tire de ce second test les conclusions suivantes : - comme lors du premier test, l'identification du meilleur candidat par similarité cosinus est moins performante que par projection - plusieurs configurations de paramètres permettent d'obtenir des performance similaires via la projection : - l2/l1 - l2/l1b - l3/l2 - l3/l2b - l3/l1b - l4/l2 - l4/l2b

[25]:
```
result_df = result_df.loc[result_df['run'] != 2.].copy()
result_df = pd.concat([result_df, pd.DataFrame(search.cv_results_)], axis=0, ignore_index=True)
result_df['run'] = result_df['run'].fillna(2)
len(result_df)
```

[25]:
```
108
```

1.2.7 Application de la Grid Search : impact des mots non vus en entrainement (run 3)

On va également voir si l'utilisation d'un vectorizer de type HashingVectorizer, qui permet de prendre en compte des mots non vus lors de l'entraînement a un impact sur la performance (ou son écart type, qui est très élevé…).

[26]:
```
process_pipe.set_params(**{'Splitter__splitter_func': splitter_funcs[2],

                          })

kwargs_to_prod = prod_params({'stop_words': {'with stopwords removal' : stop_words},
                              'ngram_range': {'bigrams': (1, 2)},
                              'binary': {'counts': False, 'binary flag': True},
                             })

param_grid = [{'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
               'SimilaritySelector__count_vect_type': ['TfidfVectorizer', 'HashingVectorizer'],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__source_norm': ['l4'],
               'SimilaritySelector__projected_norm': ['l2'],
              },
              {'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
               'SimilaritySelector__count_vect_type': ['TfidfVectorizer', 'HashingVectorizer'],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__source_norm': ['l3'],
               'SimilaritySelector__projected_norm': ['l2'],
              },
              {'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
               'SimilaritySelector__count_vect_type': ['TfidfVectorizer', 'HashingVectorizer'],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__source_norm': ['l2'],
               'SimilaritySelector__projected_norm': ['l1'],
              },
              {'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
               'SimilaritySelector__count_vect_type': ['TfidfVectorizer', 'HashingVectorizer'],
               'SimilaritySelector__similarity': ['cosine'],
              },
             ]
search = GridSearchCV(process_pipe,
```

```
                      param_grid,
                      cv=8,
                      scoring= ({'similarity': lev_scorer, 'accuracy': custom_accuracy}),
                      refit='similarity',
                      n_jobs=-1,
                      verbose=1,
                     ).fit(train, train['ingredients'])
```

```
Fitting 8 folds for each of 16 candidates, totalling 128 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   13.7s

Launching 8 processes.

[Parallel(n_jobs=-1)]: Done 128 out of 128 | elapsed:   52.8s finished
```

[27]:
```
labels = [
          '14/12',
          '13/12',
          '12/11',
          'cosine'
         ]

labels = list(product(labels, kwargs_to_prod[0], ['TfidfVectorizer', 'HashingVectorizer']))
labels = list(map(lambda x: ', '.join(x), labels))

for i in range(len(search.cv_results_['rank_test_similarity'])):
    str_result = f"{search.cv_results_['mean_test_similarity'][i]:.2%} +/- {search.
↪cv_results_['std_test_similarity'][i]:.2%}"
    print(labels[i], str_result)
```

```
14/12, with stopwords removal, bigrams, counts, TfidfVectorizer 61.11% +/- 5.30%
14/12, with stopwords removal, bigrams, counts, HashingVectorizer 52.46% +/- 3.06%
14/12, with stopwords removal, bigrams, binary flag, TfidfVectorizer 61.00% +/- 5.61%
14/12, with stopwords removal, bigrams, binary flag, HashingVectorizer 54.13% +/- 4.12%
13/12, with stopwords removal, bigrams, counts, TfidfVectorizer 61.55% +/- 5.25%
13/12, with stopwords removal, bigrams, counts, HashingVectorizer 43.37% +/- 4.64%
13/12, with stopwords removal, bigrams, binary flag, TfidfVectorizer 62.05% +/- 4.73%
13/12, with stopwords removal, bigrams, binary flag, HashingVectorizer 47.26% +/- 5.17%
12/11, with stopwords removal, bigrams, counts, TfidfVectorizer 60.86% +/- 5.65%
12/11, with stopwords removal, bigrams, counts, HashingVectorizer 57.89% +/- 5.60%
12/11, with stopwords removal, bigrams, binary flag, TfidfVectorizer 61.00% +/- 5.61%
12/11, with stopwords removal, bigrams, binary flag, HashingVectorizer 58.26% +/- 5.01%
cosine, with stopwords removal, bigrams, counts, TfidfVectorizer 54.43% +/- 7.18%
cosine, with stopwords removal, bigrams, counts, HashingVectorizer 53.01% +/- 6.20%
cosine, with stopwords removal, bigrams, binary flag, TfidfVectorizer 53.36% +/- 7.86%
cosine, with stopwords removal, bigrams, binary flag, HashingVectorizer 50.56% +/- 7.20%
```

L'utilisation d'un HashingVectorizer à la place d'un TfidfVectorizer, pour prendre en compte les mots non vus lors de l'entrainement, n'a pas d'impact positif sur la performance du modèle. Au contraire, elle semble globalement diminuer de quelques points.

[28]:
```
result_df = result_df.loc[result_df['run'] != 3.].copy()
result_df = pd.concat([result_df, pd.DataFrame(search.cv_results_)], axis=0, ignore_index=True)
result_df['run'] = result_df['run'].fillna(3)
len(result_df)
```

[28]: 124

1.2.8 Application d'une grid search : pondération des mots (run 4)

On va en plus appliquer une pondération absolue et relative des mots, dans la recherche de similarité par cosinus.

Les différentes possibilités pour le vecteur cible sont : - moyenne des vecteurs de textes des listes d'ingrédients, avec uniquement un flag binaire (présence / absence du mot) : la cible est la document frequency moyenne des mots des listes d'ingrédients - moyenne des vecteurs de textes des listes d'ingrédients, avec en prenant en compte les comptes des mots dans chacun des textes : la cible est la term frequency moyenne des mots au sein des listes d'ingrédients - moyenne des scores ``absolus'' de chacun des mots au sein des listes d'ingrédients. Il s'agit d'une ``smooth document frequency'' (elle croit logarithmiquement) - moyenne des scores ``relatifs'' de chacun des mots entre liste d'ingrédients et contenu des fiches techniques. Ici on compare la doc frequency entre les deux corpus, pour donner plus de poids aux mots qui sont plus présents dans les listes d'ingrédients que dans le reste du corps du texte.

On comparera à la projection l4/l2b, qui porte jusque là les meilleurs résultats.

[29]:
```
process_pipe.set_params(**{'Splitter__splitter_func': splitter_funcs[2],
                           'SimilaritySelector__count_vect_type': 'TfidfVectorizer',
                           })

kwargs_to_prod = prod_params({'stop_words': {'with stopwords removal' : stop_words},
                              'ngram_range': {'no_ngrams': (1, 1), 'bigrams': (1, 2)},
                              'binary': {'counts': False, 'binary flag': True},
                              'use_idf': {'without idf': False, 'with idf': True},
                              'strip_accents': {'remove accents': 'unicode'},
                             })

param_grid = [{
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
               'SimilaritySelector__scoring': ['default', 'absolute_score', 'relative_score'],
               'SimilaritySelector__similarity': ['cosine'],
              },
              {'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
               'SimilaritySelector__similarity': ['projection'],
               'SimilaritySelector__source_norm': ['l4'],
               'SimilaritySelector__projected_norm': ['l2'],
              },
             ]
search = GridSearchCV(process_pipe,
                      param_grid,
                      cv=8,
                      scoring= ({'similarity': lev_scorer, 'accuracy': custom_accuracy}),
                      refit='similarity',
                      n_jobs=-1,
                      verbose=1,
                     ).fit(train, train['ingredients'])
```

```
Fitting 8 folds for each of 32 candidates, totalling 256 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   14.4s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:  1.4min

Launching 8 processes.

[Parallel(n_jobs=-1)]: Done 256 out of 256 | elapsed:  1.8min finished
```

[30]:
```
labels = [
          'cosine',
         ]


labels = list(product(labels, kwargs_to_prod[0], ['default', 'absolute score', 'relative score']))
labels.extend(list(product(['projection l4/l2'],  kwargs_to_prod[0])))
labels = list(map(lambda x: ', '.join(x), labels))

for i in range(len(search.cv_results_['rank_test_similarity'])):
    str_result = f"{search.cv_results_['mean_test_similarity'][i]:.2%} +/- {search.
↪cv_results_['std_test_similarity'][i]:.2%}"
    print(labels[i], str_result)
```

```
cosine, with stopwords removal, no_ngrams, counts, without idf, remove accents, default 53.69% +/- 7.13%
cosine, with stopwords removal, no_ngrams, counts, without idf, remove accents, absolute score 54.47% +/-
6.87%
cosine, with stopwords removal, no_ngrams, counts, without idf, remove accents, relative score 29.42% +/-
5.32%
cosine, with stopwords removal, no_ngrams, counts, with idf, remove accents, default 55.47% +/- 6.70%
cosine, with stopwords removal, no_ngrams, counts, with idf, remove accents, absolute score 52.47% +/- 6.91%
cosine, with stopwords removal, no_ngrams, counts, with idf, remove accents, relative score 32.73% +/- 5.21%
cosine, with stopwords removal, no_ngrams, binary flag, without idf, remove accents, default 53.29% +/-
7.86%
cosine, with stopwords removal, no_ngrams, binary flag, without idf, remove accents, absolute score 54.15%
+/- 8.17%
cosine, with stopwords removal, no_ngrams, binary flag, without idf, remove accents, relative score 28.02%
+/- 5.00%
cosine, with stopwords removal, no_ngrams, binary flag, with idf, remove accents, default 54.91% +/- 7.31%
cosine, with stopwords removal, no_ngrams, binary flag, with idf, remove accents, absolute score 51.80% +/-
8.13%
cosine, with stopwords removal, no_ngrams, binary flag, with idf, remove accents, relative score 31.39% +/-
5.59%
cosine, with stopwords removal, bigrams, counts, without idf, remove accents, default 54.43% +/- 7.18%
cosine, with stopwords removal, bigrams, counts, without idf, remove accents, absolute score 55.48% +/-
7.11%
cosine, with stopwords removal, bigrams, counts, without idf, remove accents, relative score 33.39% +/-
6.11%
cosine, with stopwords removal, bigrams, counts, with idf, remove accents, default 55.86% +/- 6.78%
cosine, with stopwords removal, bigrams, counts, with idf, remove accents, absolute score 52.00% +/- 6.91%
cosine, with stopwords removal, bigrams, counts, with idf, remove accents, relative score 39.00% +/- 5.38%
cosine, with stopwords removal, bigrams, binary flag, without idf, remove accents, default 53.36% +/- 7.86%
cosine, with stopwords removal, bigrams, binary flag, without idf, remove accents, absolute score 55.36% +/-
7.36%
cosine, with stopwords removal, bigrams, binary flag, without idf, remove accents, relative score 32.74% +/-
5.87%
cosine, with stopwords removal, bigrams, binary flag, with idf, remove accents, default 54.73% +/- 7.39%
cosine, with stopwords removal, bigrams, binary flag, with idf, remove accents, absolute score 51.12% +/-
6.71%
cosine, with stopwords removal, bigrams, binary flag, with idf, remove accents, relative score 39.45% +/-
5.47%
projection l4/l2, with stopwords removal, no_ngrams, counts, without idf, remove accents 57.08% +/- 5.38%
projection l4/l2, with stopwords removal, no_ngrams, counts, with idf, remove accents 17.38% +/- 1.45%
projection l4/l2, with stopwords removal, no_ngrams, binary flag, without idf, remove accents 57.26% +/-
5.89%
projection l4/l2, with stopwords removal, no_ngrams, binary flag, with idf, remove accents 22.50% +/- 4.14%
projection l4/l2, with stopwords removal, bigrams, counts, without idf, remove accents 61.11% +/- 5.30%
projection l4/l2, with stopwords removal, bigrams, counts, with idf, remove accents 32.00% +/- 3.51%
projection l4/l2, with stopwords removal, bigrams, binary flag, without idf, remove accents 61.00% +/- 5.61%
projection l4/l2, with stopwords removal, bigrams, binary flag, with idf, remove accents 38.00% +/- 5.85%
```

[31]:
```python
result_df = result_df.loc[result_df['run'] != 4.].copy()
result_df = pd.concat([result_df, pd.DataFrame(search.cv_results_)], axis=0, ignore_index=True)
result_df['run'] = result_df['run'].fillna(4)
len(result_df)
```

[31]: 156

On en déduit : - que la similarité par projection reste le mode de détermination du candidat le plus efficace - que dans ce mode, l'utilisation de l'idf dégrade la performance - néanmoins, dans le cadre de la similarité cosinus, l'utilisation de l'idf a un impact positif pour la fonction de scoring par défaut, ou relative.

1.2.9 Application de la grid search : embeddings des mots (run 5)

On mesure l'impact sur la performance de l'utilisation d'embeddings de mots.

[32]:
```python
process_pipe.set_params(**{'Splitter__splitter_func': splitter_funcs[2],
                           'SimilaritySelector__count_vect_type': 'TfidfVectorizer',
                           })

kwargs_to_prod = prod_params({'stop_words': {'with stopwords removal' : stop_words},
```

```python
                                 'ngram_range': {'no_ngram': (1, 1)},
                                 'binary': {'counts': False, 'binary flag': True},
                                 'use_idf': {'without_idf': False, 'with_idf': True},
                                 'strip_accents': {'remove accents': 'unicode'},
                                })

param_grid = [{
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
               'SimilaritySelector__scoring': ['default', 'absolute_score', 'relative_score'],
               'SimilaritySelector__similarity': ['cosine'],
               'SimilaritySelector__embedding_method': [None, 'Word2Vec', 'tSVD'],
              },
             ]
search = GridSearchCV(process_pipe,
                      param_grid,
                      cv=8,
                      scoring= ({'similarity': lev_scorer, 'accuracy': custom_accuracy}),
                      refit='similarity',
                      n_jobs=-1,
                      verbose=1,
                      error_score='raise',
                     ).fit(train, train['ingredients'])
```

```
Fitting 8 folds for each of 36 candidates, totalling 288 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done  34 tasks      | elapsed:   27.6s
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:  2.3min

Launching 8 processes.

[Parallel(n_jobs=-1)]: Done 288 out of 288 | elapsed:  3.7min finished
```

[33]:
```python
labels = ['default', 'absolute_score', 'relative_score']



labels = list(product(kwargs_to_prod[0],
                      ['No embed', 'Word2Vec', 'tSVD'],
                      ['default', 'absolute score', 'relative score'],
                     ))
# labels.extend(list(product(['projection l4/l2'],  kwargs_to_prod[0])))
labels = list(map(lambda x: ', '.join(x), labels))

for i in range(len(search.cv_results_['rank_test_similarity'])):
    str_result = f"{search.cv_results_['mean_test_similarity'][i]:.2%} +/- {search.
 ↪cv_results_['std_test_similarity'][i]:.2%}"
    print(labels[i], str_result)
```

```
with stopwords removal, no_ngram, counts, without_idf, remove accents, No embed, default 53.69% +/- 7.13%
with stopwords removal, no_ngram, counts, without_idf, remove accents, No embed, absolute score 54.47% +/-
6.87%
with stopwords removal, no_ngram, counts, without_idf, remove accents, No embed, relative score 29.42% +/-
5.32%
with stopwords removal, no_ngram, counts, without_idf, remove accents, Word2Vec, default 53.70% +/- 6.19%
with stopwords removal, no_ngram, counts, without_idf, remove accents, Word2Vec, absolute score 53.17% +/-
5.87%
with stopwords removal, no_ngram, counts, without_idf, remove accents, Word2Vec, relative score 10.19% +/-
2.68%
with stopwords removal, no_ngram, counts, without_idf, remove accents, tSVD, default 51.60% +/- 7.44%
with stopwords removal, no_ngram, counts, without_idf, remove accents, tSVD, absolute score 49.99% +/- 7.59%
with stopwords removal, no_ngram, counts, without_idf, remove accents, tSVD, relative score 8.05% +/- 1.59%
with stopwords removal, no_ngram, counts, with_idf, remove accents, No embed, default 55.47% +/- 6.70%
with stopwords removal, no_ngram, counts, with_idf, remove accents, No embed, absolute score 52.47% +/-
6.91%
with stopwords removal, no_ngram, counts, with_idf, remove accents, No embed, relative score 32.73% +/-
5.21%
with stopwords removal, no_ngram, counts, with_idf, remove accents, Word2Vec, default 53.70% +/- 6.06%
```

```
with stopwords removal, no_ngram, counts, with_idf, remove accents, Word2Vec, absolute score 53.58% +/-
6.26%
with stopwords removal, no_ngram, counts, with_idf, remove accents, Word2Vec, relative score 10.16% +/-
2.75%
with stopwords removal, no_ngram, counts, with_idf, remove accents, tSVD, default 49.47% +/- 6.39%
with stopwords removal, no_ngram, counts, with_idf, remove accents, tSVD, absolute score 46.09% +/- 6.51%
with stopwords removal, no_ngram, counts, with_idf, remove accents, tSVD, relative score 8.96% +/- 1.99%
with stopwords removal, no_ngram, binary flag, without_idf, remove accents, No embed, default 53.29% +/-
7.86%
with stopwords removal, no_ngram, binary flag, without_idf, remove accents, No embed, absolute score 54.15%
+/- 8.17%
with stopwords removal, no_ngram, binary flag, without_idf, remove accents, No embed, relative score 28.02%
+/- 5.00%
with stopwords removal, no_ngram, binary flag, without_idf, remove accents, Word2Vec, default 53.16% +/-
6.10%
with stopwords removal, no_ngram, binary flag, without_idf, remove accents, Word2Vec, absolute score 52.54%
+/- 6.31%
with stopwords removal, no_ngram, binary flag, without_idf, remove accents, Word2Vec, relative score 10.18%
+/- 2.67%
with stopwords removal, no_ngram, binary flag, without_idf, remove accents, tSVD, default 53.84% +/- 8.26%
with stopwords removal, no_ngram, binary flag, without_idf, remove accents, tSVD, absolute score 54.32% +/-
8.38%
with stopwords removal, no_ngram, binary flag, without_idf, remove accents, tSVD, relative score 9.44% +/-
1.98%
with stopwords removal, no_ngram, binary flag, with_idf, remove accents, No embed, default 54.91% +/- 7.31%
with stopwords removal, no_ngram, binary flag, with_idf, remove accents, No embed, absolute score 51.80% +/-
8.13%
with stopwords removal, no_ngram, binary flag, with_idf, remove accents, No embed, relative score 31.39% +/-
5.59%
with stopwords removal, no_ngram, binary flag, with_idf, remove accents, Word2Vec, default 53.39% +/- 6.64%
with stopwords removal, no_ngram, binary flag, with_idf, remove accents, Word2Vec, absolute score 53.62% +/-
6.58%
with stopwords removal, no_ngram, binary flag, with_idf, remove accents, Word2Vec, relative score 10.20% +/-
2.68%
with stopwords removal, no_ngram, binary flag, with_idf, remove accents, tSVD, default 50.53% +/- 7.64%
with stopwords removal, no_ngram, binary flag, with_idf, remove accents, tSVD, absolute score 49.87% +/-
8.01%
with stopwords removal, no_ngram, binary flag, with_idf, remove accents, tSVD, relative score 9.13% +/-
2.54%
```

[34]:
```python
result_df = result_df.loc[result_df['run'] != 5].copy()
result_df = pd.concat([result_df, pd.DataFrame(search.cv_results_)], axis=0, ignore_index=True)
result_df['run'] = result_df['run'].fillna(5)
len(result_df)
```

[34]: 192

1.2.10 Random search : validation finale de l'ensemble des critères (run 6)

On applique enfin une random search, afin de voir si les conclusions qui avaient été tirée lors des explorations systématiques de certains domaines sont viables.

[35]:
```python
kwargs_to_prod = prod_params({'stop_words': {'with stopwords removal' : stop_words, 'keep stopwords': None},
                              'use_idf': {'with idf': True, 'no idf': False},
                              'binary': {'counts': False, 'binary flag': True},
                              'ngram_range': {'no_ngram': (1, 1), 'bigrams': (1, 2), 'trigrams': (1, 3)},
                              'strip_accents': {'remove accents': 'unicode', 'keep accents': None},
                             })
param_grid = [{
               'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
               'SimilaritySelector__scoring': ['default', 'absolute_score', 'relative_score'],
               'SimilaritySelector__similarity': ['cosine'],
               'SimilaritySelector__embedding_method': [None, 'Word2Vec', 'tSVD'],

              },
              {'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
```

```
                'SimilaritySelector__scoring': ['default'],
                'SimilaritySelector__similarity': ['projection'],
                'SimilaritySelector__source_norm': ['l2', 'l3', 'l4', 'l5'],
                'SimilaritySelector__projected_norm': ['l1', 'l2', 'l3', 'l4'],
               },
             ]
len(kwargs_to_prod[1])

search = RandomizedSearchCV(process_pipe,
                            param_grid,
                            n_iter=50,
                            cv=8,
                            scoring= ({'similarity': lev_scorer, 'accuracy': custom_accuracy}),
                            refit='similarity',
                            n_jobs=-1,
                            verbose=1,
                           ).fit(train, train['ingredients'])
```

```
Fitting 8 folds for each of 50 candidates, totalling 400 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.
[Parallel(n_jobs=-1)]: Done 184 tasks      | elapsed:  2.3min

Launching 8 processes.

[Parallel(n_jobs=-1)]: Done 400 out of 400 | elapsed:  6.1min finished
```

[36]:
```
search.best_params_
```

[36]:
```
{'SimilaritySelector__source_norm': 'l4',
 'SimilaritySelector__similarity': 'projection',
 'SimilaritySelector__scoring': 'default',
 'SimilaritySelector__projected_norm': 'l3',
 'SimilaritySelector__count_vect_kwargs': {'stop_words': None,
  'use_idf': False,
  'binary': True,
  'ngram_range': (1, 3),
  'strip_accents': None}}
```

[37]:
```
search.best_score_
```

[37]:
```
0.622970201742938
```

1.2.11 Tuning des méthodes de vectorisation (run 7)

[38]:
```
process_pipe.set_params(**{'Splitter__splitter_func': splitter_funcs[2],
                           })

kwargs_to_prod = prod_params({'stop_words': {'with stopwords removal' : stop_words},
                              'use_idf': {'with idf': True, 'no idf': False},
                              'binary': {'counts': False, 'binary flag': True},
                              'ngram_range': {'no_ngram': (1, 1),
                                              'bigrams': (1, 2),
                                              'trigrams': (1, 3),
                                              'quadgrams': (1, 4),
                                              'quintgrams': (1, 5)},
                              'strip_accents': {'remove accents': 'unicode'},
                             })

param_grid = [{
                'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
                'SimilaritySelector__similarity': ['cosine'],
               },
               {
                'SimilaritySelector__count_vect_kwargs': kwargs_to_prod[1],
```

```
                'SimilaritySelector__similarity': ['projection'],
                'SimilaritySelector__source_norm': ['l4'],
                'SimilaritySelector__projected_norm': ['l3'],
               }]

search = GridSearchCV(process_pipe,
                      param_grid,
                      cv=8,
                      scoring= ({'similarity': lev_scorer, 'accuracy': custom_accuracy}),
                      refit='similarity',
                      n_jobs=-1,
                      verbose=1,
                      error_score='raise',
                     ).fit(train, train['ingredients'])
```

```
Fitting 8 folds for each of 40 candidates, totalling 320 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 8 concurrent workers.

Launching 8 processes.

[Parallel(n_jobs=-1)]: Done 320 out of 320 | elapsed:  2.5min finished
```

[39]:
```
labels = list(product(['cosine', 'Proj l4/l3'],
                      kwargs_to_prod[0],
                     ))
# labels.extend(list(product(['projection l4/l2'],  kwargs_to_prod[0])))
labels = list(map(lambda x: ', '.join(x), labels))

for i in range(len(search.cv_results_['rank_test_similarity'])):
    str_result = f"{search.cv_results_['mean_test_similarity'][i]:.2%} +/- {search.
↪cv_results_['std_test_similarity'][i]:.2%}"
    print(labels[i], str_result)
```

```
cosine, with stopwords removal, with idf, counts, no_ngram, remove accents 55.47% +/- 6.70%
cosine, with stopwords removal, with idf, counts, bigrams, remove accents 55.86% +/- 6.78%
cosine, with stopwords removal, with idf, counts, trigrams, remove accents 55.01% +/- 6.50%
cosine, with stopwords removal, with idf, counts, quadgrams, remove accents 55.44% +/- 6.40%
cosine, with stopwords removal, with idf, counts, quintgrams, remove accents 55.62% +/- 6.47%
cosine, with stopwords removal, with idf, binary flag, no_ngram, remove accents 54.91% +/- 7.31%
cosine, with stopwords removal, with idf, binary flag, bigrams, remove accents 54.73% +/- 7.39%
cosine, with stopwords removal, with idf, binary flag, trigrams, remove accents 54.68% +/- 7.98%
cosine, with stopwords removal, with idf, binary flag, quadgrams, remove accents 54.23% +/- 7.59%
cosine, with stopwords removal, with idf, binary flag, quintgrams, remove accents 54.10% +/- 8.03%
cosine, with stopwords removal, no idf, counts, no_ngram, remove accents 53.69% +/- 7.13%
cosine, with stopwords removal, no idf, counts, bigrams, remove accents 54.43% +/- 7.18%
cosine, with stopwords removal, no idf, counts, trigrams, remove accents 54.26% +/- 7.21%
cosine, with stopwords removal, no idf, counts, quadgrams, remove accents 54.12% +/- 7.28%
cosine, with stopwords removal, no idf, counts, quintgrams, remove accents 54.29% +/- 7.21%
cosine, with stopwords removal, no idf, binary flag, no_ngram, remove accents 53.29% +/- 7.86%
cosine, with stopwords removal, no idf, binary flag, bigrams, remove accents 53.36% +/- 7.86%
cosine, with stopwords removal, no idf, binary flag, trigrams, remove accents 52.39% +/- 7.54%
cosine, with stopwords removal, no idf, binary flag, quadgrams, remove accents 51.73% +/- 7.89%
cosine, with stopwords removal, no idf, binary flag, quintgrams, remove accents 51.04% +/- 8.52%
Proj l4/l3, with stopwords removal, with idf, counts, no_ngram, remove accents 10.23% +/- 1.89%
Proj l4/l3, with stopwords removal, with idf, counts, bigrams, remove accents 9.05% +/- 2.18%
Proj l4/l3, with stopwords removal, with idf, counts, trigrams, remove accents 8.95% +/- 2.33%
Proj l4/l3, with stopwords removal, with idf, counts, quadgrams, remove accents 8.97% +/- 2.30%
Proj l4/l3, with stopwords removal, with idf, counts, quintgrams, remove accents 8.97% +/- 2.30%
Proj l4/l3, with stopwords removal, with idf, binary flag, no_ngram, remove accents 9.50% +/- 1.73%
Proj l4/l3, with stopwords removal, with idf, binary flag, bigrams, remove accents 9.28% +/- 2.34%
Proj l4/l3, with stopwords removal, with idf, binary flag, trigrams, remove accents 9.49% +/- 2.21%
Proj l4/l3, with stopwords removal, with idf, binary flag, quadgrams, remove accents 9.65% +/- 2.34%
Proj l4/l3, with stopwords removal, with idf, binary flag, quintgrams, remove accents 9.65% +/- 2.34%
Proj l4/l3, with stopwords removal, no idf, counts, no_ngram, remove accents 56.36% +/- 4.14%
Proj l4/l3, with stopwords removal, no idf, counts, bigrams, remove accents 59.61% +/- 4.00%
Proj l4/l3, with stopwords removal, no idf, counts, trigrams, remove accents 60.39% +/- 3.35%
```

```
Proj 14/13, with stopwords removal, no idf, counts, quadgrams, remove accents 60.72% +/- 3.33%
Proj 14/13, with stopwords removal, no idf, counts, quintgrams, remove accents 60.87% +/- 3.19%
Proj 14/13, with stopwords removal, no idf, binary flag, no_ngram, remove accents 59.16% +/- 6.49%
Proj 14/13, with stopwords removal, no idf, binary flag, bigrams, remove accents 62.61% +/- 4.29%
Proj 14/13, with stopwords removal, no idf, binary flag, trigrams, remove accents 63.31% +/- 3.83%
Proj 14/13, with stopwords removal, no idf, binary flag, quadgrams, remove accents 63.21% +/- 3.84%
Proj 14/13, with stopwords removal, no idf, binary flag, quintgrams, remove accents 63.21% +/- 3.83%
```

[40]:
```python
result_df = result_df.loc[result_df['run'] != 7.].copy()
result_df = pd.concat([result_df, pd.DataFrame(search.cv_results_)], axis=0, ignore_index=True)
result_df['run'] = result_df['run'].fillna(7)
len(result_df)
```

[40]: 232

1.2.12 Dépouillement des résultats

Préparation du dataframe On va maintenant interpréter le contenu du dataframe portant les résultats. On commence par renommer les colonnes qui ont de longs noms.

[41]:
```python
col_rename = {
              'param_SimilaritySelector__similarity': 'similarity',
              'param_Splitter__splitter_func': 'split_func',
              'param_SimilaritySelector__projected_norm': 'projected_norm',
              'param_SimilaritySelector__source_norm': 'source_norm',
              'param_SimilaritySelector__count_vect_type': 'count_vect_type',
              'param_SimilaritySelector__scoring': 'scoring',
              'param_SimilaritySelector__embedding_method': 'embedding_method',
}
result_df.rename(col_rename, axis=1, inplace=True)
```

On récupère maintenant le contenu des dictionnaires en tant que colonnes.

[42]:
```python
dict_cols = {'param_SimilaritySelector__count_vect_kwargs'}
to_concat = list()
for dict_col in dict_cols:
    to_concat.append(result_df[dict_col].apply(pd.Series))
    result_df.drop(dict_col, axis=1, inplace=True)
result_df = pd.concat([result_df, *to_concat], axis=1)
```

[43]:
```python
result_df.sample(3)
```

[43]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	similarity	split_func	params	split0_test_similarity	split1_test_similarity	split2_test_similarity	split3_test_similarity	split4_test_similarity
172	2.058746	0.053648	3.529992	0.320578	cosine	NaN	{'SimilaritySelector__count_vect_kwargs': {'st...	0.419952	0.529639	0.403381	0.388360	0.586718
58	1.581648	0.118239	1.442832	0.141242	cosine	<function split_func2 at 0x7f3a962bef70>	{'SimilaritySelector__count_vect_kwargs': {'st...	0.185499	0.295970	0.211447	0.273648	0.346027
214	1.669115	0.125986	1.156498	0.098057	projection	NaN	{'SimilaritySelector__count_vect_kwargs': {'st...	0.117025	0.075599	0.130080	0.087900	0.102976

	split5_test_similarity	split6_test_similarity	split7_test_similarity	mean_test_similarity	std_test_similarity	rank_test_similarity	split0_test_accuracy	split1_test_accuracy	split2_test_accuracy	split3_test_accuracy	split4_test_accuracy	split5_test_accuracy	split6_test_accuracy
172	0.408943	0.475325	0.474639	0.460870	0.065095	24	0.16	0.16	0.16	0.10	0.22	0.16	0.18
58	0.296101	0.272051	0.270983	0.268966	0.047056	67	0.06	0.10	0.08	0.06	0.16	0.10	0.04
214	0.073826	0.059061	0.069579	0.089493	0.023321	40	0.04	0.02	0.04	0.04	0.04	0.02	0.02

	split7_test_accuracy	mean_test_accuracy	std_test_accuracy	rank_test_accuracy	run	projected_norm	source_norm	count_vect_type	scoring	embedding_method	stop_words	ngram_range	strip_accents	binary	use_idf
172	0.14	0.16	0.031623	28	5.0	NaN	NaN	NaN	absolute_score	tSVD	{ou, le, dont, de, les, au, par, dans, pour, e...	(1, 1)	unicode	False	True
58	0.06	0.08	0.037417	63	1.0	NaN	NaN	NaN	NaN	NaN	{ou, le, dont, de, les, au, par, dans, pour, e...	(1, 2)	unicode	NaN	NaN
214	0.02	0.03	0.010000	35	7.0	13	14	NaN	NaN	NaN	{ou, le, dont, de, les, au, par, dans, pour, e...	(1, 3)	unicode	False	True

On effectue ensuite quelques prétraitements pour améliorer la lisibilité. On renomme les fonctions avec leur nom, et on applique une valeur par défaut.

[44]:
```python
def rename_funcs(func):
    try:
        return(func.__name__)
    except:
        return('split_func3')
result_df['split_func'] = result_df.loc[:, 'split_func'].apply(rename_funcs)
```

On met 2 critères pour le retrait des stopwords : retrait d'une liste, ou non retrait.

[45]:
```python
result_df['stop_words'].fillna('no_stopword_removal', inplace=True)
result_df.loc[result_df['stop_words'] != 'no_stopword_removal', 'stop_words'] = 'stop_word_list'
```

On renomme les ngram_ranges

[46]:
```python
ngram_dict = {(1, 1): 'no_ngram',
              (1, 2): 'bigrams',
              (1, 3): 'trigrams',
              (1, 4): 'quadgrams',
```

```
              (1, 5): 'quintgrams',
             }
result_df['ngram_range'] = result_df['ngram_range'].map(ngram_dict, na_action='ignore')
```

On renomme le retrait des accents.

[47]:
```
accent_dict = {None: 'no_accent_removal',
               'unicode': 'accent_removal',
              }
result_df['strip_accents'] = result_df['strip_accents'].map(accent_dict, na_action='ignore')
```

[48]:
```
result_df.drop('params', axis=1, inplace=True)
```

On renomme les embeddings

[49]:
```
embed_dict = {None: 'no_embedding',
              'Word2Vec': 'Word2Vec',
              'tSVD': 'tSVD',
              }
result_df['embedding_method'] = result_df['embedding_method'].map(embed_dict, na_action='ignore')
```

On applique ensuite les valeurs par défaut pour les colonnes sur lesquelles on n'a pas fait varier les critères.

[50]:
```
# by default, accents are stripped
result_df['strip_accents'] = result_df['strip_accents'].fillna('accent_removal')
# scoring and embedding method are not applicable if projection
result_df.loc[result_df['similarity'] == 'projection',['scoring', 'embedding_method']] = 'not_applicable'
# add default value to scoring for remainder
result_df.loc[pd.isna(result_df['scoring']), 'scoring'] = 'default'
# default value for embedding for remainder
result_df['embedding_method'] = result_df['embedding_method'].fillna('no_embedding')
# projected and source norm are not applicable if similarity is cosine
result_df.loc[result_df['similarity'] == 'cosine',['source_norm', 'projected_norm']] = 'not_applicable'
# default value for norms for remainder
result_df['source_norm'] = result_df['source_norm'].fillna('l2')
result_df['projected_norm'] = result_df['projected_norm'].fillna('l1')
```

[51]:
```
fillna_dict = {
               'similarity': 'projection',
               'split_func': 'split_func3',
               'count_vect_type': 'TfidfVectorizer',
               'use_idf': False,
               'binary': False,
              }
for key, val in fillna_dict.items():
    result_df[key] = result_df[key].fillna(val)
```

[52]:
```
parms = ['split_func',
         'stop_words',
         'strip_accents',
         'binary',
         'use_idf',
         'ngram_range',
         'similarity',
         'projected_norm',
         'source_norm',
         'count_vect_type',
         'scoring',
         'embedding_method',
        ]
result_df.reset_index().set_index(parms).drop('index', axis=1).sort_index().sample(5)
```

[52]:

split_func	stop_words	strip_accents	binary	use_idf	ngram_range	similarity	projected_norm	source_norm	count_vect_type	scoring	embedding_method	mean_fit_time	std_fit_time	mean_score_time	std_score_time	split0_test_similarity	split1_test_similarity	split2_test_similarity	split3_test_similarity	split4_test_similarity	split5_test_similarity	split6_test_similarity	split7_test_similarity	mean_test_similarity	std_test_similarity	rank_test_similarity	split0_test_accuracy	split1_test_accuracy	split2_test_accuracy	split3_test_accuracy	split4_test_accuracy	split5_test_accuracy	split6_test_accuracy	split7_test_accuracy	mean_test_accuracy	std_test_accuracy	rank_test_accuracy	run
split_func3	stop_word_list	accent_removal	True	False	bigrams	projection	l2	l2	TfidfVectorizer	not_applicable	not_applicable	1.294689	0.100355	0.902113	0.066901	0.178339	0.158652	0.168862	0.209605	0.198175	0.175983	0.130726	0.211372	0.178964	0.025517	33	0.06	0.06	0.06	0.12	0.06	0.10	0.02	0.08	0.0700	0.028284	33	2.0
			False	False	quadgrams	cosine	not_applicable	not_applicable	TfidfVectorizer	default	no_embedding	1.781962	0.128471	1.393267	0.146301	0.444685	0.647609	0.478009	0.560196	0.662707	0.518518	0.507357	0.510511	0.541199	0.072765	23	0.16	0.26	0.20	0.20	0.22	0.20	0.16	0.14	0.1925	0.035969	24	7.0
					bigrams	projection	l5	l8	TfidfVectorizer	not_applicable	not_applicable	1.184457	0.083433	0.834175	0.086871	0.464107	0.494229	0.473782	0.416605	0.486795	0.497416	0.469652	0.526745	0.478666	0.029875	32	0.16	0.16	0.22	0.14	0.18	0.22	0.18	0.12	0.1725	0.033072	32	2.0
					quintgrams	projection	l3	l4	TfidfVectorizer	not_applicable	not_applicable	2.091667	0.107070	1.043922	0.128057	0.578524	0.651197	0.552464	0.614125	0.629997	0.619385	0.583509	0.640551	0.608719	0.031869	5	0.24	0.24	0.26	0.24	0.22	0.30	0.24	0.18	0.2400	0.031623	4	7.0
					bigrams	cosine	not_applicable	not_applicable	TfidfVectorizer	default	no_embedding	1.351445	0.102006	1.293847	0.096154	0.444685	0.648166	0.478952	0.560196	0.662707	0.519592	0.510297	0.530079	0.544334	0.071784	22	0.16	0.26	0.20	0.20	0.22	0.20	0.18	0.16	0.1975	0.030721	21	1.0

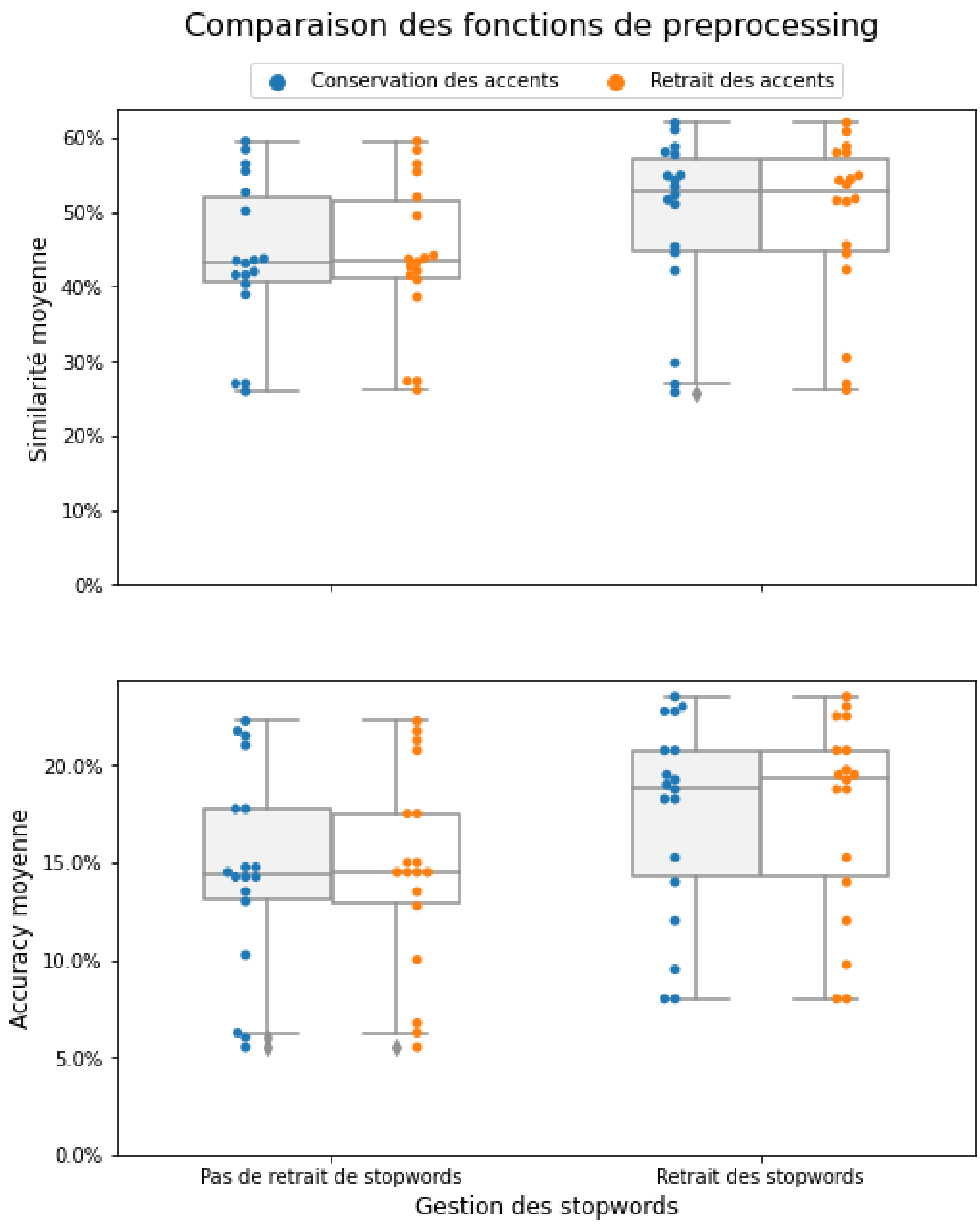
[53]:
```
result_df.to_csv(Path('.') / 'model_tuning_results.csv')
```

[54]:
```
result_df = pd.read_csv(Path('.') / 'model_tuning_results.csv')
```

Sélection des fonctions de preprocessing

[55]:
```
fig, axs = plt.subplots(nrows= 2, figsize=(8,10), sharex=True)

feats = ['mean_test_similarity', 'mean_test_accuracy']

parms = {'data': result_df.loc[result_df['run'] == 1],
         'x': 'stop_words',
         'hue': 'strip_accents',
        }

for i, feature in enumerate(feats):
    swarm = sns.swarmplot(**parms,
                          y=feature,
                          dodge=True,
        #                   color='blue',
                          ax=axs[i],
                         )

    sns.boxplot(**parms,
                y=feature,
                ax=axs[i],
                color='white',
                width=.6,
                )

    axs[i].set_ylim(0,)
    axs[i].yaxis.set_major_formatter(mtick.PercentFormatter(xmax=1.))
    axs[i].get_legend().remove()
    axs[i].set_xlabel('')

axs[1].set_xlabel('Gestion des stopwords', fontsize=12)
axs[0].set_ylabel('Similarité moyenne', fontsize=12)
axs[1].set_ylabel('Accuracy moyenne', fontsize=12)
axs[1].set_xticklabels(['Pas de retrait de stopwords', 'Retrait des stopwords'])

fig.legend(handles=axs[0].get_legend_handles_labels()[0][2:],
           labels=['Conservation des accents', 'Retrait des accents'],
           loc='center',
           ncol=2,
           bbox_to_anchor=(0, 1, 1, 0.12),
           bbox_transform=axs[0].transAxes,
          )

fig.suptitle('Comparaison des fonctions de preprocessing', fontsize=16, y=.95)

# fig.savefig(Path('..') / 'img' / 'tuning_prepro.png', bbox_inches='tight')
```

[55]:
```
Text(0.5, 0.95, 'Comparaison des fonctions de preprocessing')
```



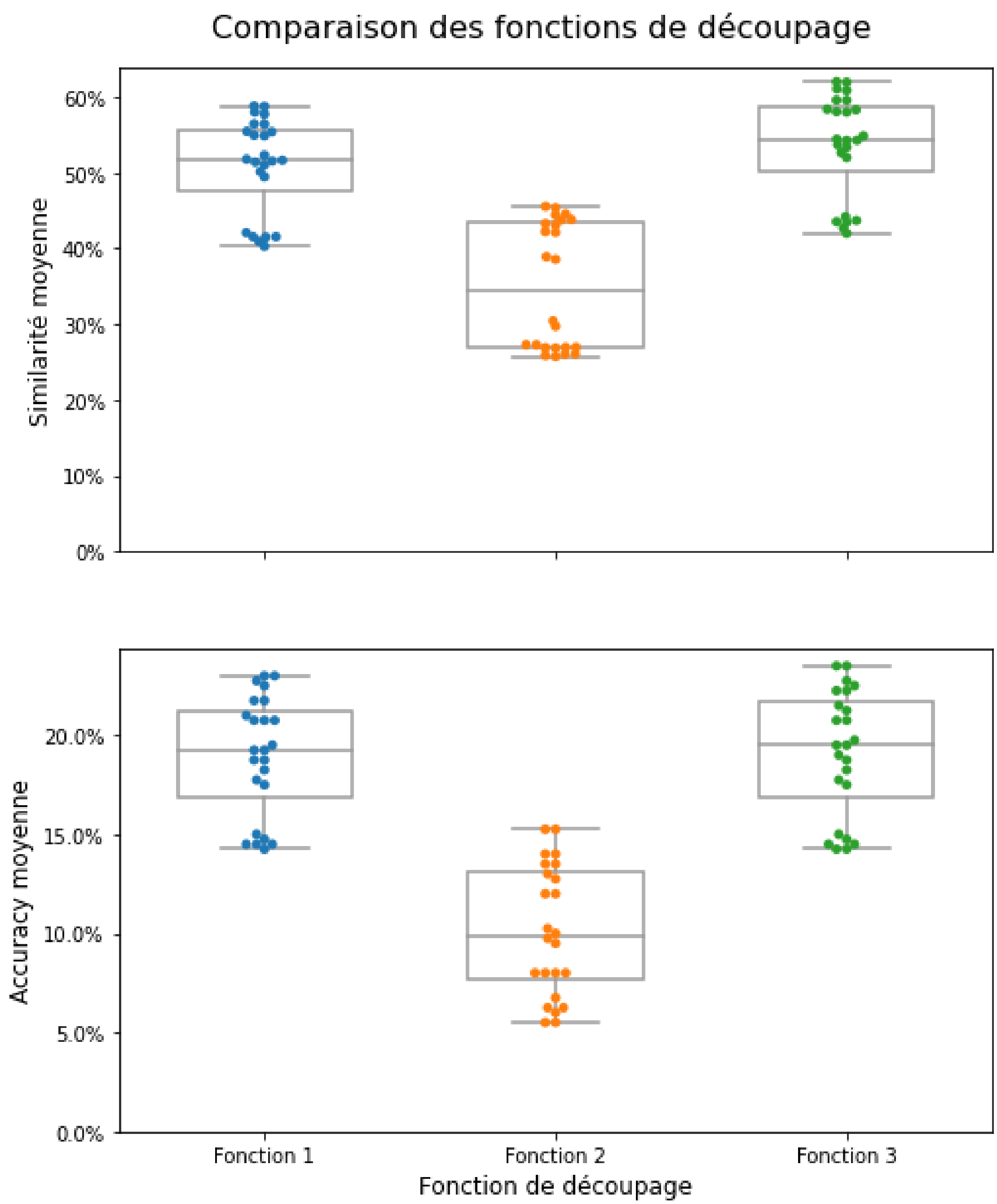
Sélection de la fonction de split

[56]:
```
fig, axs = plt.subplots(nrows= 2, figsize=(8,10), sharex=True)

feats = ['mean_test_similarity', 'mean_test_accuracy']

parms = {'data': result_df.loc[result_df['run'] == 1],
         'x': 'split_func',
         'hue': None,
```

```python
        }

for i, feature in enumerate(feats):
    swarm = sns.swarmplot(**parms,
                          y=feature,
                          dodge=True,
        #                   color='blue',
                          ax=axs[i],
                         )

    sns.boxplot(**parms,
                y=feature,
                ax=axs[i],
                color='white',
                width=.6,
                )

    axs[i].set_ylim(0,)
    axs[i].yaxis.set_major_formatter(mtick.PercentFormatter(xmax=1.))
#     axs[i].get_legend().remove()
    axs[i].set_xlabel('')

axs[1].set_xlabel('Fonction de découpage', fontsize=12)
axs[0].set_ylabel('Similarité moyenne', fontsize=12)
axs[1].set_ylabel('Accuracy moyenne', fontsize=12)
axs[1].set_xticklabels(['Fonction 1', 'Fonction 2', 'Fonction 3'])

# fig.legend(handles=axs[0].get_legend_handles_labels()[0][2:],
#            labels=['Conservation des accents', 'Retrait des accents'],
#            loc='center',
#            ncol=2,
#            bbox_to_anchor=(0, 1, 1, 0.12),
#            bbox_transform=axs[0].transAxes,
#           )

fig.suptitle('Comparaison des fonctions de découpage', fontsize=16, y=.92)

# fig.savefig(Path('..') / 'img' / 'tuning_split.png', bbox_inches='tight')
```

[56]:

```
Text(0.5, 0.92, 'Comparaison des fonctions de découpage')
```



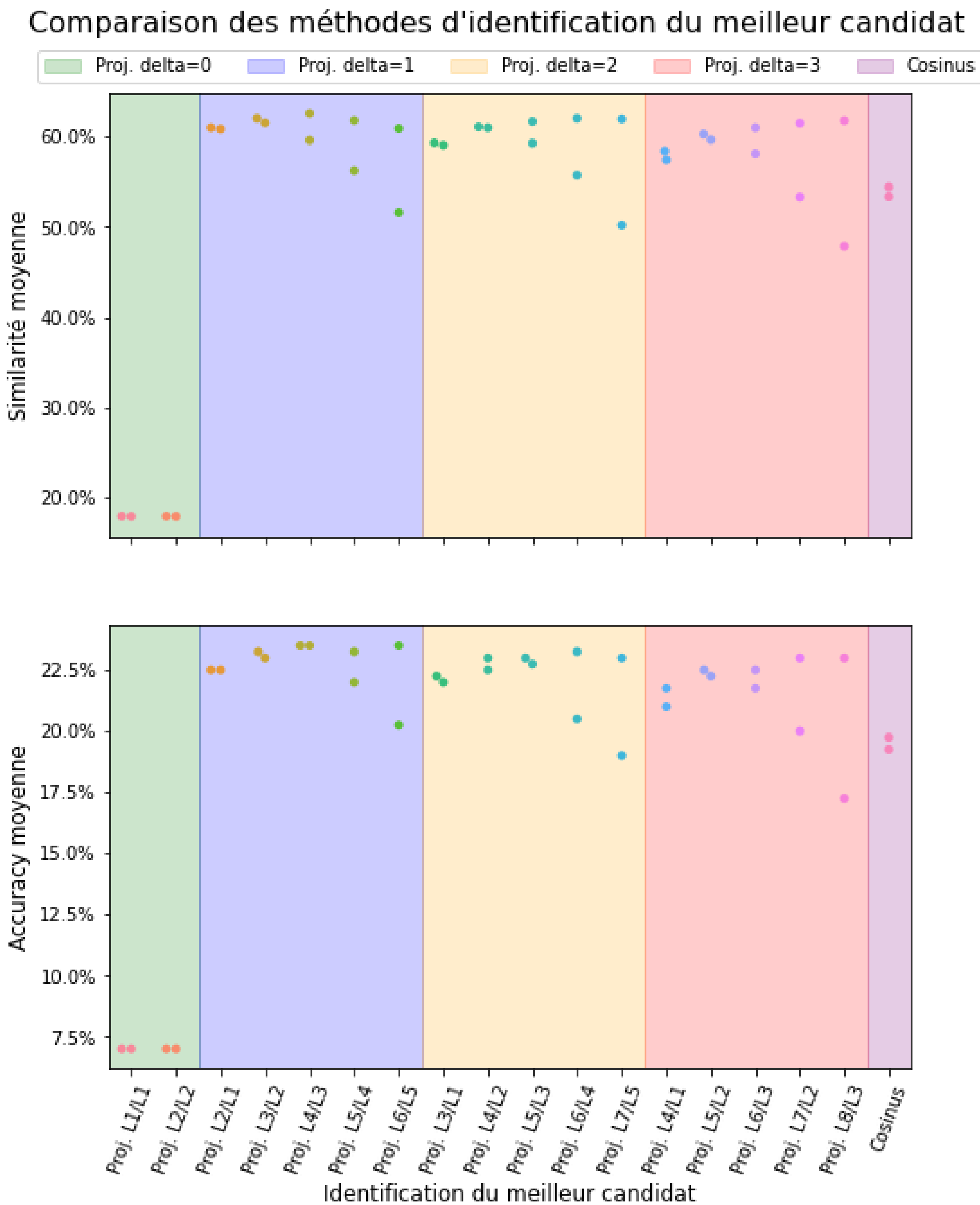
Comparatif des similarités

[57]:
```
result_df['simil_kind'] = result_df['similarity'] + result_df['source_norm'] + result_df['projected_norm']
```

[59]:
```
fig, axs = plt.subplots(nrows= 2, figsize=(8,10), sharex=True)

feats = ['mean_test_similarity', 'mean_test_accuracy']

parms = {'data': result_df.loc[(result_df['run'] == 2) &
                                (result_df['strip_accents'] == 'accent_removal') &
```

```
                             (result_df['stop_words'] == 'stop_word_list') &
                             (result_df['scoring'].isin({'default', 'not_applicable'})) &
                             (result_df['embedding_method'].isin({'no_embedding', 'not_applicable'}))],
         'x': 'simil_kind',
         'hue': None,
        }

patch_list = [
              mpatch.Rectangle((-1, 0), 2.5, 1, color='green', alpha=.2, edgecolor=None),
              mpatch.Rectangle((1.5, 0), 5, 1, color='blue', alpha=.2, edgecolor=None),
              mpatch.Rectangle((6.5, 0), 5, 1, color='orange', alpha=.2, edgecolor=None),
              mpatch.Rectangle((11.5, 0), 5, 1, color='red', alpha=.2, edgecolor=None),
              mpatch.Rectangle((16.5, 0), 2, 1, color='purple', alpha=.2, edgecolor=None),
              mpatch.Rectangle((-1, 0), 2.5, 1, color='green', alpha=.2, edgecolor=None),
              mpatch.Rectangle((1.5, 0), 5, 1, color='blue', alpha=.2, edgecolor=None),
              mpatch.Rectangle((6.5, 0), 5, 1, color='orange', alpha=.2, edgecolor=None),
              mpatch.Rectangle((11.5, 0), 5, 1, color='red', alpha=.2, edgecolor=None),
              mpatch.Rectangle((16.5, 0), 2, 1, color='purple', alpha=.2, edgecolor=None),
             ]

for i, feature in enumerate(feats):
    swarm = sns.swarmplot(**parms,
                          y=feature,
                          dodge=True,
        #                   color='blue',
                          ax=axs[i],
                         )

    axs[i].yaxis.set_major_formatter(mtick.PercentFormatter(xmax=1.))
    axs[i].set_xlabel('')
    for j in range(len(patch_list) // 2):
        axs[i].add_patch(patch_list[i * len(patch_list) // 2 + j])

axs[1].set_xlabel('Identification du meilleur candidat', fontsize=12)
axs[0].set_ylabel('Similarité moyenne', fontsize=12)
axs[1].set_ylabel('Accuracy moyenne', fontsize=12)
labels = ['Proj. L1/L1',
          'Proj. L2/L2',
          'Proj. L2/L1',
          'Proj. L3/L2',
          'Proj. L4/L3',
          'Proj. L5/L4',
          'Proj. L6/L5',
          'Proj. L3/L1',
          'Proj. L4/L2',
          'Proj. L5/L3',
          'Proj. L6/L4',
          'Proj. L7/L5',
          'Proj. L4/L1',
          'Proj. L5/L2',
          'Proj. L6/L3',
          'Proj. L7/L2',
          'Proj. L8/L3',
          'Cosinus']
plt.setp(axs[1].xaxis.get_majorticklabels(), rotation=70)
axs[1].set_xticklabels(labels)
fig.legend(handles=patch_list[len(patch_list) // 2:],
           labels=['Proj. delta=0', 'Proj. delta=1', 'Proj. delta=2', 'Proj. delta=3', 'Cosinus'],
           loc='center',
           ncol=5,
           bbox_to_anchor=(0, 1, 1, 0.12),
           bbox_transform=axs[0].transAxes,
          )

fig.suptitle("Comparaison des méthodes d'identification du meilleur candidat", fontsize=16, y=.945)

# fig.savefig(Path('..') / 'img' / 'tuning_similarite.png', bbox_inches='tight')
```

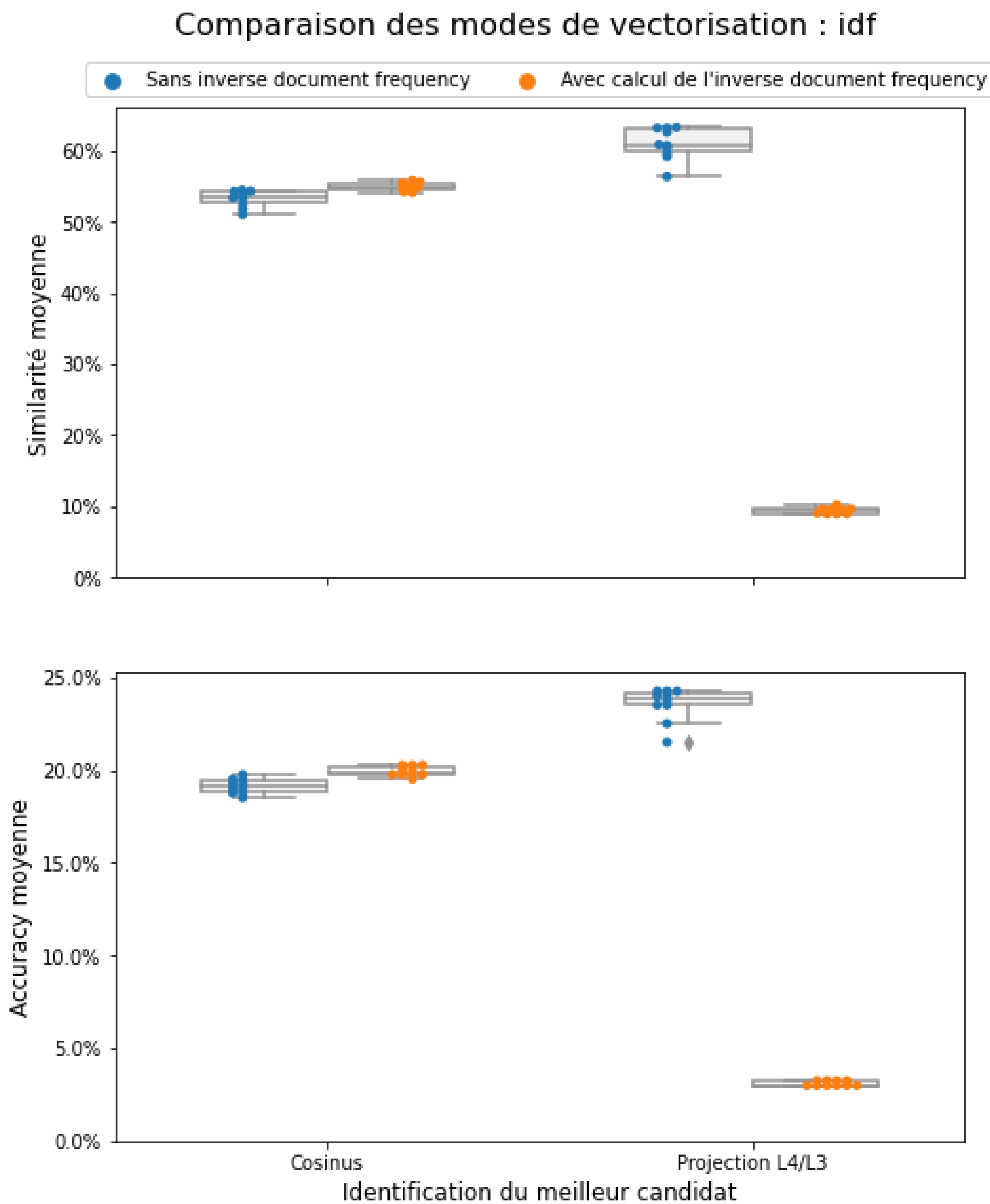
[59]: Text(0.5, 0.945, "Comparaison des méthodes d'identification du meilleur candidat")



[60]:
```
fig, axs = plt.subplots(nrows= 2, figsize=(8,10), sharex=True)

feats = ['mean_test_similarity', 'mean_test_accuracy']

parms = {'data': result_df.loc[result_df['run'] == 7],
          'x': 'similarity',
          'hue': 'use_idf',
```

```
        }

for i, feature in enumerate(feats):
    swarm = sns.swarmplot(**parms,
                          y=feature,
                          dodge=True,
        #                   color='blue',
                          ax=axs[i],
                         )

    sns.boxplot(**parms,
                y=feature,
                ax=axs[i],
                color='white',
                width=.6,
                )

    axs[i].set_ylim(0,)
    axs[i].yaxis.set_major_formatter(mtick.PercentFormatter(xmax=1.))
    axs[i].get_legend().remove()
    axs[i].set_xlabel('')

axs[1].set_xlabel('Identification du meilleur candidat', fontsize=12)
axs[0].set_ylabel('Similarité moyenne', fontsize=12)
axs[1].set_ylabel('Accuracy moyenne', fontsize=12)
axs[1].set_xticklabels(['Cosinus', 'Projection L4/L3'])

fig.legend(handles=axs[0].get_legend_handles_labels()[0][2:],
           labels=["Sans inverse document frequency", "Avec calcul de l'inverse document frequency"],
           loc='center',
           ncol=2,
           bbox_to_anchor=(0, 1, 1, 0.12),
           bbox_transform=axs[0].transAxes,
          )

fig.suptitle('Comparaison des modes de vectorisation : idf', fontsize=16, y=.95)

# fig.savefig(Path('..') / 'img' / 'tuning_idf.png', bbox_inches='tight')
```

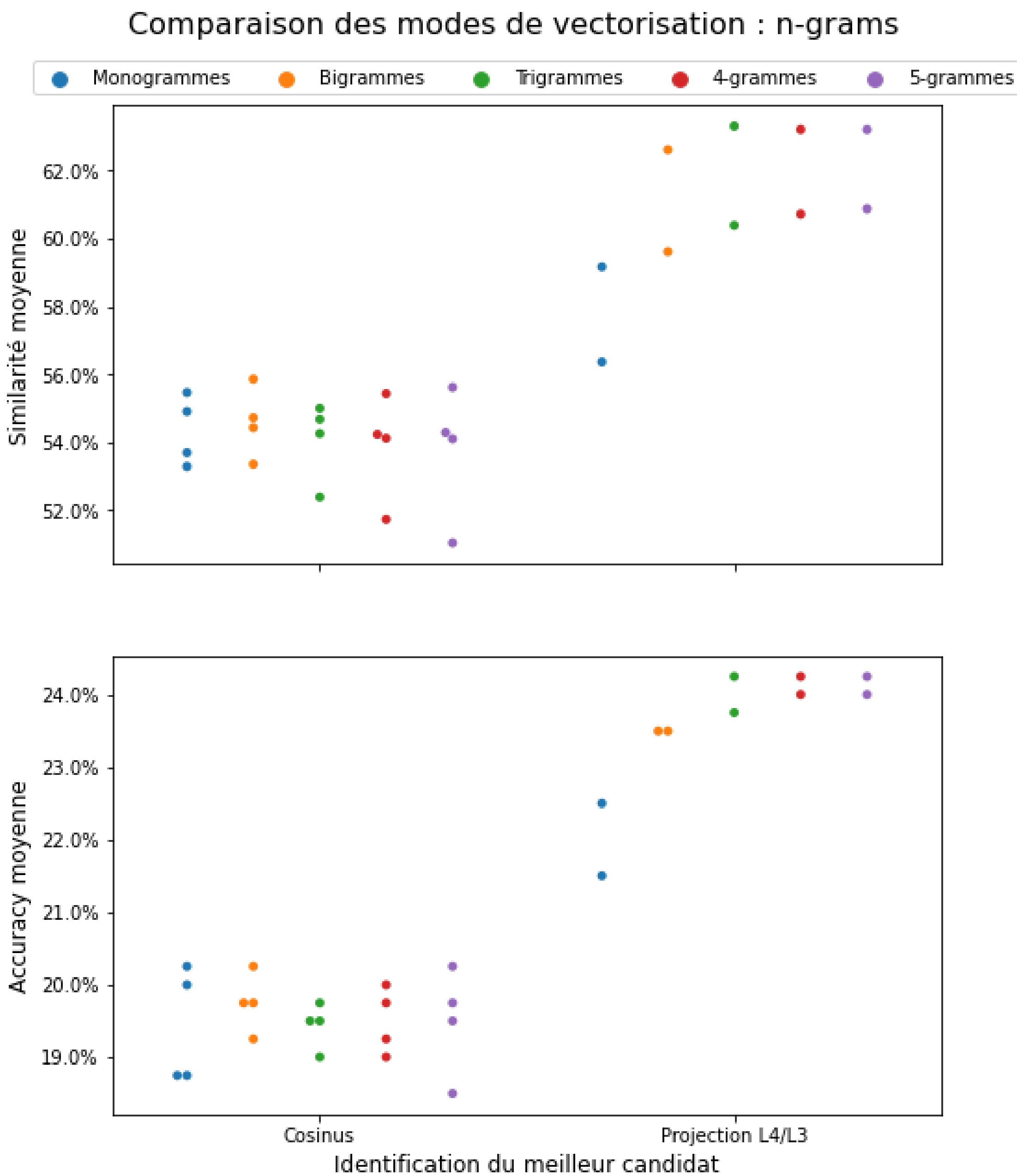
[60]:
```
Text(0.5, 0.95, 'Comparaison des modes de vectorisation : idf')
```



[61]:
```
fig, axs = plt.subplots(nrows= 2, figsize=(8,10), sharex=True)

feats = ['mean_test_similarity', 'mean_test_accuracy']

parms = {'data': result_df.loc[(result_df['run'] == 7) &
                                ((result_df['similarity'] == 'cosine') | # & result_df['use_idf'] |
                                 (result_df['similarity'] == 'projection') & ~result_df['use_idf'])
                               ],
         'x': 'similarity',
         'hue': 'ngram_range',
```

```python
        }

for i, feature in enumerate(feats):
    swarm = sns.swarmplot(**parms,
                          y=feature,
                          dodge=True,
        #                   color='blue',
                          ax=axs[i],
                         )

#     sns.boxplot(**parms,
#                 y=feature,
#                 ax=axs[i],
#                 color='white',
#                 width=.6,
#                 )

#     axs[i].set_ylim(0,)
    axs[i].yaxis.set_major_formatter(mtick.PercentFormatter(xmax=1.))
    axs[i].get_legend().remove()
    axs[i].set_xlabel('')

axs[1].set_xlabel('Identification du meilleur candidat', fontsize=12)
axs[0].set_ylabel('Similarité moyenne', fontsize=12)
axs[1].set_ylabel('Accuracy moyenne', fontsize=12)
axs[1].set_xticklabels(['Cosinus', 'Projection L4/L3'])

fig.legend(handles=axs[0].get_legend_handles_labels()[0][:],
           labels=['Monogrammes', 'Bigrammes', 'Trigrammes', '4-grammes', '5-grammes'],
           loc='center',
           ncol=5,
           bbox_to_anchor=(0, 1, 1, 0.12),
           bbox_transform=axs[0].transAxes,
          )

fig.suptitle('Comparaison des modes de vectorisation : n-grams', fontsize=16, y=.95)

# fig.savefig(Path('..') / 'img' / 'tuning_ngrams.png', bbox_inches='tight')
```

[61]:
```
Text(0.5, 0.95, 'Comparaison des modes de vectorisation : n-grams')
```



[62]:
```
# fig, axs = plt.subplots(nrows= 2, figsize=(8,10), sharex=True)

feats = ['mean_test_similarity', 'mean_test_accuracy']

parms = {'data': result_df.loc[(result_df['run'] == 5)
                              ],
         'x': 'scoring',
         'hue': 'use_idf',
        }

for i, feature in enumerate(feats):
    swarm = sns.swarmplot(**parms,
                          y=feature,
```

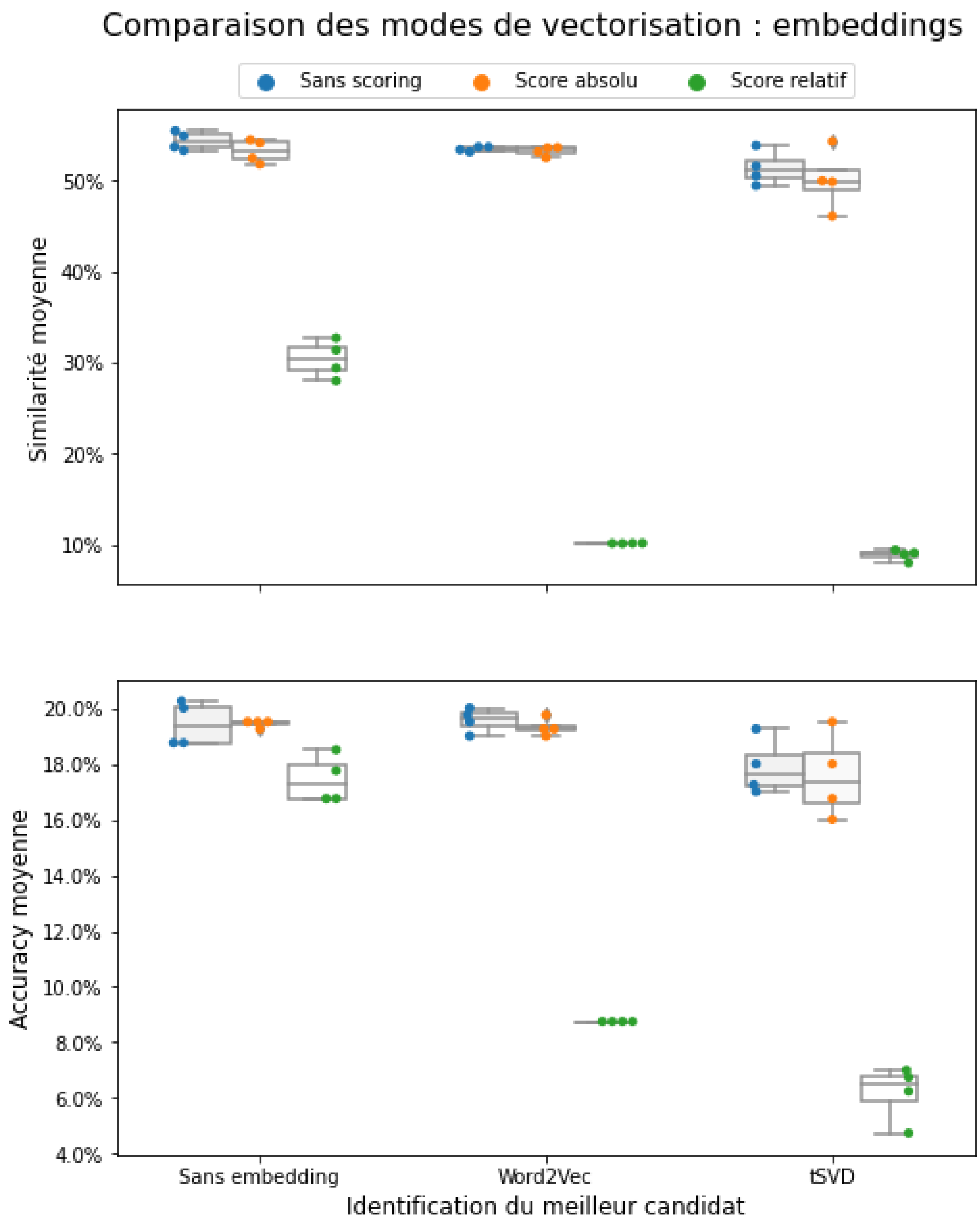
```
                         dodge=True,
        #                  color='blue',
                         ax=axs[i],
                        )

    sns.boxplot(**parms,
                y=feature,
                ax=axs[i],
                color='white',
                width=.6,
                )

#     axs[i].set_ylim(0,)
    axs[i].yaxis.set_major_formatter(mtick.PercentFormatter(xmax=1.))
    axs[i].get_legend().remove()
    axs[i].set_xlabel('')

axs[1].set_xlabel('Identification du meilleur candidat', fontsize=12)
axs[0].set_ylabel('Similarité moyenne', fontsize=12)
axs[1].set_ylabel('Accuracy moyenne', fontsize=12)
axs[1].set_xticklabels(['Sans score', 'Score absolu', 'Score relatif'])

fig.legend(handles=axs[0].get_legend_handles_labels()[0][2:],
           labels=["Sans idf", "Avec calcul de l'idf"],
           loc='center',
           ncol=5,
           bbox_to_anchor=(0, 1, 1, 0.12),
           bbox_transform=axs[0].transAxes,
          )

fig.suptitle('Comparaison des modes de vectorisation : Scores spécifiques', fontsize=16, y=.95)

# fig.savefig(Path('..') / 'img' / 'tuning_score.png', bbox_inches='tight')
```

[62]: Text(0.5, 0.95, 'Comparaison des modes de vectorisation : Scores spécifiques')

[63]:
```
fig, axs = plt.subplots(nrows= 2, figsize=(8,10), sharex=True)

feats = ['mean_test_similarity', 'mean_test_accuracy']

parms = {'data': result_df.loc[(result_df['run'] == 5)
                              ],
         'x': 'embedding_method',
         'hue': 'scoring',
        }

for i, feature in enumerate(feats):
    swarm = sns.swarmplot(**parms,
                         y=feature,
                         dodge=True,
        #                  color='blue',
                         ax=axs[i],
                        )

    sns.boxplot(**parms,
                y=feature,
                ax=axs[i],
                color='white',
                width=.6,
                )

#     axs[i].set_ylim(0,)
    axs[i].yaxis.set_major_formatter(mtick.PercentFormatter(xmax=1.))
    axs[i].get_legend().remove()
    axs[i].set_xlabel('')

axs[1].set_xlabel('Identification du meilleur candidat', fontsize=12)
```

```python
axs[0].set_ylabel('Similarité moyenne', fontsize=12)
axs[1].set_ylabel('Accuracy moyenne', fontsize=12)
axs[1].set_xticklabels(['Sans embedding', 'Word2Vec', 'tSVD'])

fig.legend(handles=axs[0].get_legend_handles_labels()[0][3:],
           labels=["Sans scoring", "Score absolu", "Score relatif"],
           loc='center',
           ncol=5,
           bbox_to_anchor=(0, 1, 1, 0.12),
           bbox_transform=axs[0].transAxes,
          )

fig.suptitle('Comparaison des modes de vectorisation : embeddings', fontsize=16, y=.95)

# fig.savefig(Path('..') / 'img' / 'tuning_embedding.png', bbox_inches='tight')
```

[63]:
```
Text(0.5, 0.95, 'Comparaison des modes de vectorisation : embeddings')
```



1.3 Evaluation finale

On évalue la performance du modèle avec les meilleurs paramètres sur le set de test, après entraînement sur le set d'entrainement.

[64]:
```
parm_dict = {'Splitter__splitter_func': splitter_funcs[2],
             'SimilaritySelector__count_vect_type': 'TfidfVectorizer',
             'SimilaritySelector__similarity': 'projection',
             'SimilaritySelector__source_norm': 'l4',
```

```
            'SimilaritySelector__projected_norm': 'l3',
            'SimilaritySelector__count_vect_kwargs': {'ngram_range': (1, 3),
                                                       'stop_words': stop_words,
                                                       'strip_accents': 'unicode',
                                                       'binary': True,
                                                       'use_idf': False,
                                                      }




           }

process_pipe.set_params(**parm_dict)
process_pipe.fit(train, train['ingredients'])
print(f"Levenshtein similarity at final evaluation: {lev_scorer(process_pipe, test, test['ingredients']):.
↪2%}")
print(f"Accuracy at final evaluation: {custom_accuracy(process_pipe, test, test['ingredients']):.2%}")
```

```
Launching 8 processes.
Launching 8 processes.
Levenshtein similarity at final evaluation: 67.18%
Launching 8 processes.
Accuracy at final evaluation: 27.00%
```

[65]:
```
predicted = process_pipe.predict(test)
lev_sim = partial(text_similarity, similarity='levenshtein')
```

```
Launching 8 processes.
```

[66]:
```
comparison = (predicted.rename('Predicted')
                       .to_frame()
                       .join(test['ingredients'])
                       .rename({'ingredients': 'Target'}, axis=1))
comparison['Similarity'] = comparison.apply(lambda x: f"{lev_sim(x['Predicted'], x['Target']):.2%}", axis=1)
comparison.sample(5)
```

[66]:

uid	Predicted	Target	Similarity
e51b7fd6-d878-47f8-a36b-f10f8d4087bd	1/2 1/4 1/8 1/16 1/32	Débris de truffes d'hiver, jus de truffes, sel	13.04%
f45db604-11ad-4756-aeab-3a5a1a34f914	Ingrédients: sucre; sirop de glucose; dextrose...	sucre; sirop de glucose; dextrose; gélatine; a...	93.58%
2ca5dc9e-8058-499a-affe-3ec9c06d55b7	Gastronome \n70%A/30% R	100% Arabica	9.09%
2286f782-9d2e-410f-84c4-4ab88003a002	INGREDIENTS: Pêches et poires en cubes (avec l...	Pêches et poires en cubes (avec leur jus d'ori...	92.80%
21233a00-bc20-40fc-acb9-ee2e2321cac2	Boisson gazeuse aromatisée au jus de fruit à b...		0.00%

[67]:
```
with pd.option_context("max_colwidth", 2100):
    tex_str = (
    comparison.replace(r'^\s*$', np.nan, regex=True)
              .to_latex(index=False,
                        index_names=False,
                        column_format='p{9cm}p{9cm}c',
                        na_rep='<rien>',
                        longtable=True,
                        header=["Liste d'ingrédients prédite", "Liste d'ingrédients cible", "Sim."],
                        label='tbl:final_prediction',
                        caption="Prédictions du meilleur modèle sur le set de test",
                       )
              .replace(r'\textbackslash n', r' \newline ')
              .replace(r'\\', r'\\ \hline')
    )
# with open(Path('..') / 'tbls' / 'final_prediction.tex', 'w') as file:
#     file.write(tex_str)
```