Projet_ML_FakeNews

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1 MACHINE LEARNING - PROJET

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[65]:
```
from google.colab import drive
import sys
drive.mount('/content/gdrive/')
my_local_drive='/content/gdrive/My Drive/Colab Notebooks/MachineLearning'
# Ajout du path pour les librairies, fonctions et données
sys.path.append(my_local_drive)
# Se positionner sur le répertoire associé
%cd $my_local_drive

%pwd
```

```
Drive already mounted at /content/gdrive/; to attempt to forcibly remount, call
drive.mount("/content/gdrive/", force_remount=True).
/content/gdrive/My Drive/Colab Notebooks/MachineLearning
```

[65]: '/content/gdrive/My Drive/Colab Notebooks/MachineLearning'

Tout d'abord, on importe les librairies nécessaires.

[66]:
```
!pip install contractions

import sklearn

import warnings
warnings.filterwarnings("ignore", category=FutureWarning)

import nltk
nltk.download('averaged_perceptron_tagger')
nltk.download('omw-1.4')
nltk.download('wordnet')
nltk.download('stopwords')

import numpy as np
import pandas as pd
```

```python
import contractions
import matplotlib as mpl
import matplotlib.pyplot as plt

from nltk.corpus import wordnet
from nltk.stem import WordNetLemmatizer
from nltk.tokenize import RegexpTokenizer
from nltk.corpus import stopwords

from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.metrics import accuracy_score
from sklearn import metrics
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import precision_recall_fscore_support as score
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.utils import resample

from PIL import Image

from wordcloud import WordCloud, STOPWORDS
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: contractions in /usr/local/lib/python3.10/dist-
packages (0.1.73)
Requirement already satisfied: textsearch>=0.0.21 in
/usr/local/lib/python3.10/dist-packages (from contractions) (0.0.24)
Requirement already satisfied: anyascii in /usr/local/lib/python3.10/dist-
packages (from textsearch>=0.0.21->contractions) (0.3.2)
Requirement already satisfied: pyahocorasick in /usr/local/lib/python3.10/dist-
packages (from textsearch>=0.0.21->contractions) (2.0.0)
```

```
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /root/nltk_data…
[nltk_data]   Package averaged_perceptron_tagger is already up-to-
[nltk_data]       date!
[nltk_data] Downloading package omw-1.4 to /root/nltk_data…
[nltk_data]   Package omw-1.4 is already up-to-date!
[nltk_data] Downloading package wordnet to /root/nltk_data…
[nltk_data]   Package wordnet is already up-to-date!
```

```
[nltk_data] Downloading package stopwords to /root/nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

Ensuite, on lit les données (training set). On lira le testing set une fois qu'on aura trouvé un modèle de classification et qu'il faudra le tester.

[67]:
```python
training_data = pd.read_csv("HAI817_Projet_train.csv")
training_data.head()
```

[67]:
```
  public_id                                               text  \
0  5a228e0e  Distracted driving causes more deaths in Canad…
1  30c605a1  Missouri politicians have made statements afte…
2  c3dea290  Home Alone 2: Lost in New York is full of viol…
3  f14e8eb6  But things took a turn for the worse when riot…
4  faf024d6  It's no secret that Epstein and Schiff share a…

                                               title our rating
0  You Can Be Fined $1,500 If Your Passenger Is U…      false
1      Missouri lawmakers condemn Las Vegas shooting    mixture
2  CBC Cuts Donald Trump's 'Home Alone 2' Cameo O…    mixture
3  Obama's Daughters Caught on Camera Burning US …      false
4  Leaked Visitor Logs Reveal Schiff's 78 Visits …      false
```

[68]:
```python
training_data.tail()
```

[68]:
```
     public_id                                               text  \
1259  47423bb6  More than four million calls to the taxman are…
1260  097c142a  More under-18s are being taken to court for se…
1261  08bc59f4  The Government's much vaunted Help to Buy Isa …
1262  af3393ce  The late Robin Williams once called cocaine "G…
1263  a39d07df  The late Robin Williams once called cocaine "G…

                                                  title our rating
1259  Taxman fails to answer four million calls a ye…       true
1260  Police catch 11-year-olds being used to sell d…       true
1261  Help to Buy Isa scandal: 500,000 first-time bu…      false
1262           A coke-snorting generation of hypocrites       true
1263           A coke-snorting generation of hypocrites       true
```

[69]:
```python
training_data.shape
```

[69]: `(1264, 4)`

1.1 Phase de preprocessing

Durant cette phase, on va créer plusieurs fonctions permettant de prétraiter nos données. Voici ces fonctions: - contractions (e.g. it's := it is) - get regex tokens - lower casing - process numbers - remove stop words - remove indesirable words - lemmatization

Après ça, on va pouvoir créer des dataframes contenant nos données textuelles prétraitées par des combinaisons de nos méthodes (pour tester quelles méthodes sont les plus efficaces).

Nous cherchons à présent, à traiter les contractions présentes au sein de nos textes.

[70]:
```
def processContractions(data) :
  text_to_tokenize = []
  for text_content in data.text :
    phrase = contractions.fix(text_content)
    text_to_tokenize.append(phrase)
  return text_to_tokenize
```

Prétraitons maintenant les données. On commence par mettre tous les mots en minuscules. Pour cela, trouvons d'abord la liste des mots (tokens) contenues dans les textes à traiter.

[71]:
```
tokenizer = RegexpTokenizer(r"(\w+|#\d|\?|!)|.|:|;")

def getRegexTokens(data_texts):
  tokens = []

  for text_content in data_texts:
    regex = tokenizer.tokenize(text_content)
    #print(regex)
    for reg in regex:
      if not reg == '':
        tokens.append(reg)

  return tokens
```

[72]:
```
#for text_content in training_data.text:
#  for token in text_content.split():
#    tokens.append(token)
```

[73]:
```
def getRegexTokens4oneText(one_text):
  tokens = []

  regex = tokenizer.tokenize(one_text)
  for reg in regex:
    if not reg == '':
      tokens.append(reg)

  return tokens
```

[74]:
```
def allToLowerCase(tokens):
  for i in range(len(tokens)):
    tokens[i] = tokens[i].lower()
  return tokens
```

Traitement des valeurs numériques en "number"

[75]:
```
def processNumbers(tokens):
  processed_tokens = ["number" if token.isnumeric() else token for token in␣
↪tokens]
  return processed_tokens
```

Après, on élimine les 'stops-words' en anglais. Ceux-ci n'apportent généralement pas (ou très peu) de significtion au texte.

[76]:
```
def removeStopWords(tokens):
  stop_words = set(stopwords.words('english'))
  text_without_stopWords = [word for word in tokens if not word in stop_words]
  return text_without_stopWords

def removeIndesirableWords(tokens):
  indesirable_list = ['!','?
↪','a','b','c','d','e','f','g','h','i','j','k','l','m','n','o','p','q','r','s','t','u','v','
  text_without_indesirables = [word for word in tokens if not word in␣
↪indesirable_list]
  return text_without_indesirables
```

On va maintenant faire de la lemmatization, ce qui va permettre de garder le racine des mots utiliser afin de la comparer plus facilement et de réduire la taille du vocabulaire.

[77]:
```
def get_wordnet_pos(word):
    tag = nltk.pos_tag([word])[0][1][0].upper()
    tag_dict = {"J": wordnet.ADJ,
                "N": wordnet.NOUN,
                "V": wordnet.VERB,
                "R": wordnet.ADV}

    return tag_dict.get(tag, wordnet.NOUN)
```

[78]:
```
def createVoc(tokens):
  out = {}
  for token in tokens:
    if token in out.keys():
      out[token] += 1
    else:
      out[token] = 1
  return out
```

[79]:
```
# première methode de preprocessing
# contraction, regex, lower case, process numbers,
# remove stop words, remove indesirable words, lemmatization
def preprocess1(data):

  newData = pd.DataFrame()
```

```
  lemma = WordNetLemmatizer()
  for i in range(len(data.text)):
    temp = getRegexTokens4oneText(data.text.iloc[i])
    temp = allToLowerCase(temp)
    temp = processNumbers(temp)
    temp = removeStopWords(temp)
    temp = removeIndesirableWords(temp)
    for j in range(len(temp)):
      temp[j] = lemma.lemmatize(temp[j], pos=get_wordnet_pos(temp[j]))
    s = " ".join(temp)
    newData.at[i, 'text'] = s
  return newData
```

[80]:
```
# deuxième methode de preprocessing
# c'est ici qu'on va tester différentes combinaisons de méthodes de␣
↪preprocessing
def preprocess2(data):

  newData = pd.DataFrame()
  lemma = WordNetLemmatizer()
  for i in range(len(data.text)):
    temp = getRegexTokens4oneText(data.text.iloc[i])
    temp = allToLowerCase(temp)
    #temp = processNumbers(temp)
    temp = removeStopWords(temp)
    #temp = removeIndesirableWords(temp)

    for j in range(len(temp)):
      temp[j] = lemma.lemmatize(temp[j], pos=get_wordnet_pos(temp[j]))

    s = " ".join(temp)
    newData.at[i, 'text'] = s
  return newData
```

[81]:
```
def createVocToDF(data):
  tokens = []

  for text_content in data.text:
    for token in text_content.split():
      tokens.append(token)

  # create vocabulary after preprocessing
  voc_after_prepro = createVoc(tokens)

  data_items = voc_after_prepro.items()
  data_list = list(data_items)
  df = pd.DataFrame(data_list)
```

```
    #df.to_csv('vocabulary_after_preprocessing.csv')
    return df
```

Maintenant on va juste appliquer ces méthodes de préprocessing sur nos données de différentes manières.

[82]:
```
# on applique la contraction de mots d'office dès le début
td_contracted = training_data.copy()
td_contracted.text = processContractions(td_contracted)

# données avec toutes les méthodes de preprocessing appliquées
td_preprocessed1 = td_contracted.copy()
td_preprocessed1.text = preprocess1(td_preprocessed1)
```

[83]:
```
print(td_preprocessed1.text[0])
```

```
distract drive cause death canada impaired drive every province territory law
drive operating cell phone tell passenger stay phone drive measure necessary
distract drive claimed life impaired drive province like british columbia
ontario quebec alberta nova scotia manitoba newfoundland labrador mobile phone
even held passenger dangerous distraction driver start next week distract screen
held passenger attracts penalty number number three demerit point driver screen
mix matter hold device use facetime take selfies driver show driver funny cat
video province mobile phone categorise visual display unit meaning consider akin
television screen important practice safe drive sake fellow driver canada crack
distract drive problem rollout stricter law impose harsher penalty heftier fine
guilty offender take effect next week add serious penalty convict distract drive
```

[84]:
```
# total vocabulary from all texts (preprocessed1)
df_preprocessed1 = createVocToDF(td_preprocessed1)
df_preprocessed1.head()
```

[84]:

	0	1
0	distract	16
1	drive	221
2	cause	547
3	death	646
4	canada	123

[85]:
```
td_preprocessed2 = td_contracted.copy()
td_preprocessed2.text = preprocess2(td_preprocessed2)
```

[86]:
```
print(td_preprocessed2.text[0])
```

```
distract drive cause death canada impaired drive every province territory law
drive operating cell phone tell passenger stay phone drive measure necessary
distract drive claimed life impaired drive province like british columbia
```

```
ontario quebec alberta nova scotia manitoba newfoundland labrador mobile phone
even held passenger dangerous distraction driver start next week distract screen
held passenger attracts penalty 1 500 three demerit point driver screen mix
matter hold device use facetime take selfies driver show driver funny cat video
province mobile phone categorise visual display unit meaning consider akin
television screen important practice safe drive sake fellow driver canada crack
distract drive problem rollout stricter law impose harsher penalty heftier fine
guilty offender take effect next week add serious penalty convict distract drive
```

1.2 Visualisations

Dans cette phase de visualitions on va afficher des informations pertinentes comme les mots récurrents d'une certaine classe, ou encore la taille du dictionnaire avant et après prétraitement, etc.

Tout d'abord, créons des dictionnaires pour les labels False/True/Mixture/Other. Cela va nous permettre d'identifier les mots clés d'une classe et d'une autre.

[87]:
```python
def createTrueFalseVoc(data):
  false_voc = {}
  true_voc = {}
  mixt_voc = {}
  other_voc = {}
  for i in range(len(data.text)):
    temp = data.text.iloc[i].split()
    if data['our rating'].iloc[i] == 'false':
      for token in temp:
        if token in false_voc:
          false_voc[token] += 1
        else:
          false_voc[token] = 1
    elif data['our rating'].iloc[i] == 'true':
      for token in temp:
        if token in true_voc:
          true_voc[token] += 1
        else:
          true_voc[token] = 1
    elif data['our rating'].iloc[i] == 'mixture':
      for token in temp:
        if token in mixt_voc:
          mixt_voc[token] += 1
        else:
          mixt_voc[token] = 1
    elif data['our rating'].iloc[i] == 'other':
      for token in temp:
        if token in other_voc:
          other_voc[token] += 1
        else:
          other_voc[token] = 1
```

```
    return false_voc, true_voc, mixt_voc, other_voc
```

[88]:
```
false_voc, true_voc , mixt_voc, other_voc = createTrueFalseVoc(td_preprocessed1)
```

[1]:
```
#print(false_voc)
```

[2]:
```
#print(true_voc)
```

[3]:
```
#print(mixt_voc)
```

[ ]:
```
#print(other_voc)
```

[93]:
```
# WORD CLOUD

cmap_O = mpl.cm.Oranges(np.linspace(0,1,20))
cmap_O = mpl.colors.ListedColormap(cmap_O[10:,:-1])

#Font parameters for our Title
font = {'family': 'serif',
        'color':  'darkred',
        'weight': 'normal',
        'size': 36,}

# Mask for the Word Cloud
stop_words=set(STOPWORDS)
stop_words.add("number")
stop_words.add("say")
```

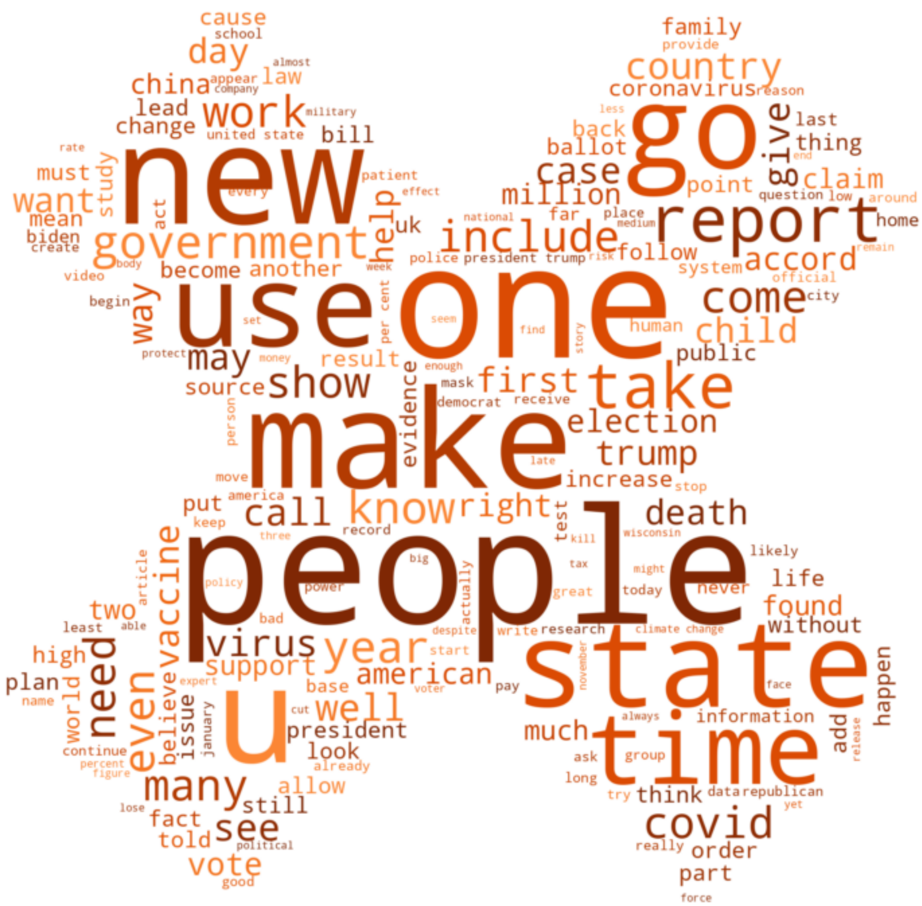
[94]:
```
# WORD CLOUD TRUE VOC

cb_mask_TRUE = np.array(Image.open('yes.jpg'))

#Creating variable with data for this Word Cloud
temp = td_preprocessed1[td_preprocessed1['our rating'] == 'true']
textS = ' '.join(temp['text'].tolist())

cb_wc=WordCloud(width=400,height=200,mask=cb_mask_TRUE,random_state=101,␣
 ↪max_font_size=450,
                 min_font_size=3,stopwords=stop_words,background_color="white",
                 scale=3,max_words=200,collocations=True,colormap=cmap_O)

#Generate it
cb_wc.generate(str(textS))

fig=plt.figure(figsize=(20,20))
plt.ylim(-400,2700)
plt.gca().invert_yaxis()
```

```python
plt.axis("off")
plt.imshow(cb_wc,interpolation='bilinear')
plt.show()
```


year
one
make
people
state
time
work
uk
new
government
child
change
news
picture
increase
country
school
include
high
take
see
report
give
need
use
well
know
lead
march
come
rise
world
first
record
warm
many
even
want
help
much
way
life
go
show
may

[95]:

```python
# WORD CLOUD FALSE VOC

cb_mask_FALSE = np.array(Image.open('croix.jpg'))

#Creating variable with data for this Word Cloud
temp = td_preprocessed1[td_preprocessed1['our rating'] == 'false']
textS = ' '.join(temp['text'].tolist())

cb_wc=WordCloud(width=400,height=200,mask=cb_mask_FALSE,random_state=101,␣
↪max_font_size=450,
                 min_font_size=3,stopwords=stop_words,background_color="white",
                 scale=3,max_words=200,collocations=True,colormap=cmap_O)

#Generate it
cb_wc.generate(str(textS))

fig=plt.figure(figsize=(15,15))
plt.ylim(-400,2700)
plt.gca().invert_yaxis()
plt.axis("off")
plt.imshow(cb_wc,interpolation='bilinear')
plt.show()
```


people
make
one
use
new
go
state
time
u
report
take
include
government
know
right
call
death
covid
year
virus
need
vaccine
even
many
see
show
first
election
trump
come
child
accord
country
coronavirus
family
work
day
china
want
case
million
ballot
back
give
claim
thing
last
point
home
help
way
may
source
result
evidence
increase
life
found
without
happen
information
think
order
part
much
well
president
american
support
two
high
plan
world
believe
issue
fact
told
still
vote
allow
look
cause
law
lead
change
bill
must
study
mean
biden
become
another
follow
system
public
human
put
test
test
likely
never
today
research
add
group
republican
ask
long
data
really

[96]:

```
# WORD CLOUD MIXTURE

cb_mask_FALSE = np.array(Image.open('mixture.jpg'))

#Creating variable with data for this Word Cloud
temp = td_preprocessed1[td_preprocessed1['our rating'] == 'mixture']
textS = ' '.join(temp['text'].tolist())

cb_wc=WordCloud(width=400,height=200,mask=cb_mask_FALSE,random_state=101,␣
 ↪max_font_size=450,
                 min_font_size=3,stopwords=stop_words,background_color="white",
                 scale=3,max_words=200,collocations=True,colormap=cmap_0)

#Generate it
cb_wc.generate(str(textS))

fig=plt.figure(figsize=(15,15))
plt.ylim(-400,2700)
plt.gca().invert_yaxis()
plt.axis("off")
plt.imshow(cb_wc,interpolation='bilinear')
plt.show()
```


state
people
new
time
make
one
year
need
go
government
include
climate change
increase
school
country
support
know
see
right
well
work
report
child
million
think
today
help
cost
plan
use
many
world
may
high
even
change
show
take
come
call
much
law
job
family
public
new york
teacher
provide
first
still
back
accord
u

[97]:

```
# WORD CLOUD OTHER

cb_mask_FALSE = np.array(Image.open('other.jpg'))

#Creating variable with data for this Word Cloud
temp = td_preprocessed1[td_preprocessed1['our rating'] == 'other']
textS = ' '.join(temp['text'].tolist())

cb_wc=WordCloud(width=400,height=200,mask=cb_mask_FALSE,random_state=101,␣
↪max_font_size=450,
                 min_font_size=3,stopwords=stop_words,background_color="white",
                 scale=3,max_words=200,collocations=True,colormap=cmap_O)

#Generate it
cb_wc.generate(str(textS))

fig=plt.figure(figsize=(15,15))
plt.ylim(-400,2700)
plt.gca().invert_yaxis()
plt.axis("off")
plt.imshow(cb_wc,interpolation='bilinear')
plt.show()
```


people
one
year
new
report
child
time
make
include
take
call
vaccine
study
work
day
come
use
go
many
state
know
give
vote
change
two
uk
help
merck
need
government
even
see
life
well
first
patient
data
post
research
increase
look
service
support
care
trump
show
high
election
death
diabetes
president
climate
group
million
temperature
accord
mean
country
record
another
biden
benefit
claim
rise
stock
cause
told
company
case
britain
happen
found
three
lead
large
become
short seller
may
result
percent
system
right
problem
end
receive

1.3 Classifications

kNN

Naive Bayes

Logistic Regression

Decision Tree

D'abord, on applique les mêmes transformations au testing data

[98]:
```
test_data = pd.read_csv("HAI817_Projet_test.csv")
test_data.text = processContractions(test_data)
testd_preprocessed1 = test_data.copy();
testd_preprocessed1.text = preprocess1(test_data);

testd_preprocessed2 = test_data.copy();
testd_preprocessed2.text = preprocess2(test_data);
```

1.3.1 TF-IDF / Count vectorizer

[212]:
```
# comment/uncomment ci-dessous pour faire changer de vectorizer

#cv = TfidfVectorizer(max_df=0.8, min_df=0.2, ngram_range=(1,3))
#cv = TfidfVectorizer(ngram_range=(2,2))
cv = TfidfVectorizer()
#cv = CountVectorizer()

# CATEGORIE A: True vs False vs Mixture vs Other
X_traincv1_A = td_preprocessed1.text
y_traincv1_A = td_preprocessed1['our rating']
X_testcv1_A = testd_preprocessed1.text
y_testcv1_A = testd_preprocessed1['our rating']

X_traincv1_A = cv.fit_transform(X_traincv1_A)
X_testcv1_A = cv.transform(X_testcv1_A)

# CATEGORIE B: True vs False
X_traincv1_B = td_preprocessed1.loc[((td_preprocessed1['our rating'] == 'true'␣
↪) | (td_preprocessed1['our rating'] == 'false'))].text
y_traincv1_B = td_preprocessed1.loc[((td_preprocessed1['our rating'] == 'true'␣
↪) | (td_preprocessed1['our rating'] == 'false'))]['our rating']
X_testcv1_B = testd_preprocessed1.loc[((testd_preprocessed1['our rating'] ==␣
↪'true' ) | (testd_preprocessed1['our rating'] == 'false'))].text
```

```
y_testcv1_B = testd_preprocessed1.loc[((testd_preprocessed1['our rating'] ==␣
↪'true' ) | (testd_preprocessed1['our rating'] == 'false'))]['our rating']

X_traincv1_B = cv.fit_transform(X_traincv1_B)
X_testcv1_B = cv.transform(X_testcv1_B)

# CATEGORIE C: True/False vs Other/Mixture
td_TFvO = td_preprocessed1.copy(True);
td_TFvO.loc[((td_preprocessed1['our rating'] == 'true' ) |␣
↪(td_preprocessed1['our rating'] == 'false')), 'our rating'] = 'tf'
testd_TFvO = testd_preprocessed1.copy(True);
testd_TFvO.loc[((testd_preprocessed1['our rating'] == 'true' ) |␣
↪(testd_preprocessed1['our rating'] == 'false')), 'our rating'] = 'tf'

td_TFvOBis = td_preprocessed1.copy(True);
td_TFvOBis.loc[((td_preprocessed1['our rating'] == 'other' ) |␣
↪(td_preprocessed1['our rating'] == 'mixture')), 'our rating'] = 'om'
testd_TFvOBis = testd_preprocessed1.copy(True);
testd_TFvOBis.loc[((testd_preprocessed1['our rating'] == 'other' ) |␣
↪(testd_preprocessed1['our rating'] == 'mixture')), 'our rating'] = 'om'

X_traincv1_C = td_TFvO.loc[((td_TFvO['our rating'] == 'tf' )|( td_TFvOBis['our␣
↪rating'] == 'om'))].text
y_traincv1_C = td_TFvO.loc[((td_TFvO['our rating'] == 'tf') | (td_TFvOBis['our␣
↪rating'] == 'om'))]['our rating']
X_testcv1_C = testd_TFvO.loc[((testd_TFvO['our rating'] == 'tf') |␣
↪(testd_TFvOBis['our rating'] == 'om'))].text
y_testcv1_C = testd_TFvO.loc[((testd_TFvO['our rating'] == 'tf') |␣
↪(testd_TFvOBis['our rating'] == 'om'))]['our rating']

X_traincv1_C = cv.fit_transform(X_traincv1_C)
X_testcv1_C = cv.transform(X_testcv1_C)
```

Maintenant, on fait la même chose mais pour la deuxième méthode de préprocessing (càd sans la lemmatization)

[213]:
```
# CATEGORIE A: True vs False vs Mixture vs Other
X_traincv2_A = td_preprocessed2.text
y_traincv2_A = td_preprocessed2['our rating']
X_testcv2_A = testd_preprocessed2.text
y_testcv2_A = testd_preprocessed2['our rating']

X_traincv2_A = cv.fit_transform(X_traincv2_A)
X_testcv2_A = cv.transform(X_testcv2_A)

# CATEGORIE B: True vs False
```

```
X_traincv2_B = td_preprocessed2.loc[((td_preprocessed2['our rating'] == 'true'␣
 ↪) | (td_preprocessed2['our rating'] == 'false'))].text
y_traincv2_B = td_preprocessed2.loc[((td_preprocessed2['our rating'] == 'true'␣
 ↪) | (td_preprocessed2['our rating'] == 'false'))]['our rating']
X_testcv2_B = testd_preprocessed2.loc[((testd_preprocessed2['our rating'] ==␣
 ↪'true' ) | (testd_preprocessed2['our rating'] == 'false'))].text
y_testcv2_B = testd_preprocessed2.loc[((testd_preprocessed2['our rating'] ==␣
 ↪'true' ) | (testd_preprocessed2['our rating'] == 'false'))]['our rating']

X_traincv2_B = cv.fit_transform(X_traincv2_B)
X_testcv2_B = cv.transform(X_testcv2_B)

# CATEGORIE C: True/False vs Other
td_TFv02 = td_preprocessed2.copy(True);
td_TFv02.loc[((td_preprocessed2['our rating'] == 'true' ) |␣
 ↪(td_preprocessed2['our rating'] == 'false')), 'our rating'] = 'tf'
testd_TFv02 = testd_preprocessed2.copy(True);
testd_TFv0.loc[((testd_preprocessed2['our rating'] == 'true' ) |␣
 ↪(testd_preprocessed2['our rating'] == 'false')), 'our rating'] = 'tf'
X_traincv2_C = td_TFv02.loc[((td_TFv02['our rating'] == 'tf' )|( td_TFv02['our␣
 ↪rating'] == 'other'))].text
y_traincv2_C = td_TFv02.loc[((td_TFv02['our rating'] == 'tf') | (td_TFv02['our␣
 ↪rating'] == 'other'))]['our rating']
X_testcv2_C = testd_TFv02.loc[((testd_TFv02['our rating'] == 'tf') |␣
 ↪(testd_TFv02['our rating'] == 'other'))].text
y_testcv2_C = testd_TFv02.loc[((testd_TFv02['our rating'] == 'tf') |␣
 ↪(testd_TFv02['our rating'] == 'other'))]['our rating']

X_traincv2_C = cv.fit_transform(X_traincv2_C)
X_testcv2_C = cv.transform(X_testcv2_C)
```

1.3.2 kNN

[214]:
```
model = KNeighborsClassifier(n_neighbors=3, p=1) # take odd nr > 2 to avoid␣
 ↪tights

model.fit(X_traincv1_A, y_traincv1_A)

y_pred_train = model.predict(X_traincv1_A)
y_pred_test = model.predict(X_testcv1_A)

print('Accuracy on training data =', accuracy_score(y_traincv1_A, y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_A, y_pred_test))
print('')
print(metrics.classification_report(y_testcv1_A, y_pred_test))
```

```
Accuracy on training data = 0.7919303797468354
Accuracy on testing data = 0.5147058823529411

              precision    recall  f1-score   support

       false       0.51      1.00      0.68       315
     mixture       0.00      0.00      0.00        56
       other       0.00      0.00      0.00        31
        true       0.00      0.00      0.00       210

    accuracy                           0.51       612
   macro avg       0.13      0.25      0.17       612
weighted avg       0.26      0.51      0.35       612


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[215]:
```
model = KNeighborsClassifier(n_neighbors=3, p=1) # take odd nr > 2 to avoid␣
↪tights

model.fit(X_traincv1_B, y_traincv1_B)

y_pred_train = model.predict(X_traincv1_B)
y_pred_test = model.predict(X_testcv1_B)

print('Accuracy on training data =', accuracy_score(y_traincv1_B, y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_B, y_pred_test))
print('')
print(metrics.classification_report(y_testcv1_B, y_pred_test))
```

```
Accuracy on training data = 0.779467680608365
Accuracy on testing data = 0.6

              precision    recall  f1-score   support
```

```
       false       0.60      1.00      0.75       315
        true       0.00      0.00      0.00       210

    accuracy                           0.60       525
   macro avg       0.30      0.50      0.37       525
weighted avg       0.36      0.60      0.45       525

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[216]:

```
model = KNeighborsClassifier(n_neighbors=3, p=1) # take odd nr > 2 to avoid␣
 ↪tights
# d'autres valeurs pour n_neighbors ont été testées, 3 s'est avéré la meilleure

model.fit(X_traincv1_C, y_traincv1_C)

y_pred_train = model.predict(X_traincv1_C)
y_pred_test = model.predict(X_testcv1_C)

print('Accuracy on training data =', accuracy_score(y_traincv1_C, y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_C, y_pred_test))
print('')
print(metrics.classification_report(y_testcv1_C, y_pred_test))
```

```
Accuracy on training data = 0.928006329113924
Accuracy on testing data = 0.8578431372549019

              precision    recall  f1-score   support

     mixture       0.00      0.00      0.00        56
       other       0.00      0.00      0.00        31
          tf       0.86      1.00      0.92       525
```

```
    accuracy                           0.86       612
   macro avg       0.29      0.33      0.31       612
weighted avg       0.74      0.86      0.79       612

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

1.3.3 Naive Bayes

[217]:
```
model = MultinomialNB(alpha=0, force_alpha=True) # no smoothing

model.fit(X_traincv1_A, y_traincv1_A)

y_pred_train = model.predict(X_traincv1_A)
y_pred_test = model.predict(X_testcv1_A)

print('Accuracy on training data =', accuracy_score(y_traincv1_A, y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_A, y_pred_test))
print('')
print(metrics.classification_report(y_testcv1_A, y_pred_test))
```

```
Accuracy on training data = 0.9849683544303798
Accuracy on testing data = 0.5163398692810458

              precision    recall  f1-score   support

       false       0.52      1.00      0.68       315
     mixture       0.00      0.00      0.00        56
       other       0.00      0.00      0.00        31
        true       1.00      0.01      0.02       210

    accuracy                           0.52       612
   macro avg       0.38      0.25      0.17       612
weighted avg       0.61      0.52      0.36       612
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/naive_bayes.py:907:
RuntimeWarning: divide by zero encountered in log
  self.feature_log_prob_ = np.log(smoothed_fc) - np.log(
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[218]:

```
model = MultinomialNB(alpha=0, force_alpha=True) # no smoothing

model.fit(X_traincv1_B, y_traincv1_B)

y_pred_train = model.predict(X_traincv1_B)
y_pred_test = model.predict(X_testcv1_B)

print('Accuracy on training data =', accuracy_score(y_traincv1_B, y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_B, y_pred_test))
print('')
print(metrics.classification_report(y_testcv1_B, y_pred_test))
```

```
Accuracy on training data = 0.9949302915082383
Accuracy on testing data = 0.6076190476190476

              precision    recall  f1-score   support

       false       0.61      1.00      0.75       315
        true       0.83      0.02      0.05       210

    accuracy                           0.61       525
   macro avg       0.72      0.51      0.40       525
weighted avg       0.70      0.61      0.47       525


/usr/local/lib/python3.10/dist-packages/sklearn/naive_bayes.py:907:
RuntimeWarning: divide by zero encountered in log
  self.feature_log_prob_ = np.log(smoothed_fc) - np.log(
```

[219]:

```python
model = MultinomialNB(alpha=0, force_alpha=True) # no smoothing

model.fit(X_traincv1_C, y_traincv1_C)

y_pred_train = model.predict(X_traincv1_C)
y_pred_test = model.predict(X_testcv1_C)

print('Accuracy on training data =', accuracy_score(y_traincv1_C, y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_C, y_pred_test))
print('')
print(metrics.classification_report(y_testcv1_C, y_pred_test))
```

```
Accuracy on training data = 0.990506329113924
Accuracy on testing data = 0.24019607843137256

              precision    recall  f1-score   support

     mixture       0.09      0.80      0.16        56
       other       0.00      0.00      0.00        31
          tf       0.86      0.19      0.32       525

    accuracy                           0.24       612
   macro avg       0.32      0.33      0.16       612
weighted avg       0.74      0.24      0.29       612

/usr/local/lib/python3.10/dist-packages/sklearn/naive_bayes.py:907:
RuntimeWarning: divide by zero encountered in log
  self.feature_log_prob_ = np.log(smoothed_fc) - np.log(
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

1.3.4 Logistic Regression

[220]:
```
model = LogisticRegression(max_iter=1000)

lr = model.fit(X_traincv1_A, y_traincv1_A)

y_pred_train = lr.predict(X_traincv1_A)
y_pred_test = lr.predict(X_testcv1_A)

print('Accuracy on training data =', accuracy_score(y_traincv1_A, y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_A, y_pred_test))
print('')
print(metrics.classification_report(y_testcv1_A, y_pred_test))
```

```
Accuracy on training data = 0.8251582278481012
Accuracy on testing data = 0.5065359477124183

              precision    recall  f1-score   support

       false       0.54      0.95      0.69       315
     mixture       0.11      0.11      0.11        56
       other       0.00      0.00      0.00        31
        true       0.80      0.02      0.04       210

    accuracy                           0.51       612
   macro avg       0.36      0.27      0.21       612
weighted avg       0.56      0.51      0.38       612

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[221]:
```
model = LogisticRegression(max_iter=1000)

lr = model.fit(X_traincv1_B, y_traincv1_B)
```

```
y_pred_train = lr.predict(X_traincv1_B)
y_pred_test = lr.predict(X_testcv1_B)

print('Accuracy on training data =', accuracy_score(y_traincv1_B, y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_B, y_pred_test))
print('')
print(metrics.classification_report(y_testcv1_B, y_pred_test))
```

```
Accuracy on training data = 0.8415716096324461
Accuracy on testing data = 0.6190476190476191

              precision    recall  f1-score   support

       false       0.61      0.99      0.76       315
        true       0.86      0.06      0.11       210

    accuracy                           0.62       525
   macro avg       0.73      0.53      0.43       525
weighted avg       0.71      0.62      0.50       525
```

[222]:

```
model = LogisticRegression(max_iter=1000)

lr = model.fit(X_traincv1_C, y_traincv1_C)

y_pred_train = lr.predict(X_traincv1_C)
y_pred_test = lr.predict(X_testcv1_C)

print('Accuracy on training data =', accuracy_score(y_traincv1_C, y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_C, y_pred_test))
print('')
print(metrics.classification_report(y_testcv1_C, y_pred_test))
```

```
Accuracy on training data = 0.8330696202531646
Accuracy on testing data = 0.8431372549019608

              precision    recall  f1-score   support

     mixture       0.09      0.02      0.03        56
       other       0.00      0.00      0.00        31
          tf       0.86      0.98      0.91       525

    accuracy                           0.84       612
   macro avg       0.32      0.33      0.31       612
weighted avg       0.74      0.84      0.79       612
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

1.3.5 Decision Tree

```
[ ]: grid_param = {'max_depth': [50],'criterion': ['gini',␣
      ↪'entropy'],'min_samples_leaf': [5]}

     gd_sr = GridSearchCV(estimator=DecisionTreeClassifier(),
     param_grid=grid_param,
     scoring='accuracy',
     cv=10,
     n_jobs=-1,
     return_train_score=True)
     dt = gd_sr.fit(X_traincv1_A, y_traincv1_A)

     y_pred_train = dt.predict(X_traincv1_A)
     y_pred_test = dt.predict(X_testcv1_A)

     print('Accuracy on training data =', accuracy_score(y_traincv1_A, y_pred_train))
     print('Accuracy on testing data =', accuracy_score(y_testcv1_A, y_pred_test))
     print('')
     print(metrics.classification_report(y_testcv1_A, y_pred_test))
```

```
[ ]: dt = gd_sr.fit(X_traincv1_B, y_traincv1_B)

     y_pred_train = dt.predict(X_traincv1_B)
     y_pred_test = dt.predict(X_testcv1_B)

     print('Accuracy on training data =', accuracy_score(y_traincv1_B, y_pred_train))
     print('Accuracy on testing data =', accuracy_score(y_testcv1_B, y_pred_test))
     print('')
```

[ ]:
```
dt = gd_sr.fit(X_traincv1_C, y_traincv1_C)

y_pred_train = dt.predict(X_traincv1_C)
y_pred_test = dt.predict(X_testcv1_C)

print('Accuracy on training data =', accuracy_score(y_traincv1_C, y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_C, y_pred_test))
print('')
```

1.3.6 Random Forest

[ ]:
```
# Random forest
model = RandomForestClassifier(random_state=42)

rf = model.fit(X_traincv1_B, y_traincv1_B)

y_pred_train = rf.predict(X_traincv1_B)
y_pred_test = rf.predict(X_testcv1_B)

print('Accuracy on training data =', metrics.accuracy_score(y_traincv1_B,␣
 ↪y_pred_train))
print('Accuracy on test data =', metrics.accuracy_score(y_testcv1_B,␣
 ↪y_pred_test))
print('')
print(metrics.classification_report(y_testcv1_B, y_pred_test))
```

1.4 Test résultats

Dans cette section on va tester plein de choses pour tenter d'améliorer les résultats.

[225]:
```
model = KNeighborsClassifier(n_neighbors=3, p=1) # take odd nr > 2 to avoid␣
 ↪tights

model.fit(X_traincv2_B, y_traincv2_B)

y_pred_train = model.predict(X_traincv2_B)
y_pred_test = model.predict(X_testcv2_B)

print('Accuracy on training data =', accuracy_score(y_traincv2_B, y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv2_B, y_pred_test))
print('')
print(metrics.classification_report(y_testcv2_B, y_pred_test))
```

```
Accuracy on training data = 0.779467680608365
Accuracy on testing data = 0.6

              precision    recall  f1-score   support
```

```
       false       0.60      1.00      0.75       315
        true       0.00      0.00      0.00       210

    accuracy                           0.60       525
   macro avg       0.30      0.50      0.37       525
weighted avg       0.36      0.60      0.45       525

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[226]:
```
model = MultinomialNB(alpha=0.01)

model.fit(X_traincv2_B, y_traincv2_B)

y_pred_train = model.predict(X_traincv2_B)
y_pred_test = model.predict(X_testcv2_B)

print('Accuracy on training data =', accuracy_score(y_traincv2_B, y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv2_B, y_pred_test))
print('')
print(metrics.classification_report(y_testcv2_B, y_pred_test))
```

```
Accuracy on training data = 0.991128010139417
Accuracy on testing data = 0.6704761904761904

              precision    recall  f1-score   support

       false       0.65      0.96      0.78       315
        true       0.80      0.23      0.36       210

    accuracy                           0.67       525
   macro avg       0.73      0.60      0.57       525
weighted avg       0.71      0.67      0.61       525
```

[227]:
```python
model = MultinomialNB(alpha=0.01)

model.fit(X_traincv2_A, y_traincv2_A)

y_pred_train = model.predict(X_traincv2_A)
y_pred_test = model.predict(X_testcv2_A)

print('Accuracy on training data =', accuracy_score(y_traincv2_A, y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv2_A, y_pred_test))
print('')
print(metrics.classification_report(y_testcv2_A, y_pred_test))
```

```
Accuracy on training data = 0.9762658227848101
Accuracy on testing data = 0.5245098039215687

              precision    recall  f1-score   support

       false       0.58      0.92      0.71       315
     mixture       0.17      0.25      0.20        56
       other       0.00      0.00      0.00        31
        true       0.67      0.09      0.15       210

    accuracy                           0.52       612
   macro avg       0.35      0.31      0.27       612
weighted avg       0.54      0.52      0.44       612
```

[228]:
```python
dt = gd_sr.fit(X_traincv2_B, y_traincv2_B)

y_pred_train = dt.predict(X_traincv2_B)
y_pred_test = dt.predict(X_testcv2_B)

print('Accuracy on training data =', accuracy_score(y_traincv2_B, y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv2_B, y_pred_test))
print('')
```

```
Accuracy on training data = 0.9721166032953105
Accuracy on testing data = 0.5828571428571429
```

1.4.1 Downsampling / upsampling

Problème de déséquilibre des classes dans notre training data ? On va donc voir on a combien de documents classés comme Vrai et combien comme Faux.

[229]:
```
true_count = (td_preprocessed1['our rating'] == 'true').
 ↪value_counts(normalize=False)[True]
false_count = (td_preprocessed1['our rating'] == 'false').
 ↪value_counts(normalize=False)[True]
other_count = (td_preprocessed1['our rating'] == 'other').
 ↪value_counts(normalize=False)[True]
mix_count = (td_preprocessed1['our rating'] == 'mixture').
 ↪value_counts(normalize=False)[True]
print(true_count)
print(false_count)
print(other_count)
print(mix_count)
```

```
211
578
117
358
```

Effectivement il y a un gros déséquilibre, on va donc faire du downsampling pour avoir 211 articles vrais et 211 articles faux. Cela devrait améliorer nos résultats.

[230]:
```
# Créer dataframe qui contient que les documents True ou False
td_p1_TF = td_preprocessed1.loc[((td_preprocessed1['our rating'] == 'true' ) |␣
 ↪(td_preprocessed1['our rating'] == 'false'))]
count_labels = td_p1_TF.groupby('our rating').count()

# DOWNSAMPLING
# categorie B (True vs False)
n_samples = count_labels.min().iloc[0]

td_p1_TF_down = td_p1_TF.groupby('our rating').apply(lambda x: x.
 ↪sample(n_samples)).reset_index(drop=True)

true_count_down = (td_p1_TF_down['our rating'] == 'true').
 ↪value_counts(normalize=False)[True]
false_count_down = (td_p1_TF_down['our rating'] == 'false').
 ↪value_counts(normalize=False)[True]
print(true_count_down)
print(false_count_down)
```

```
211
211
```

[231]:
```
# UPSAMPLING
# categorie B

n_samples = count_labels.max().iloc[0]
```

```
td_p1_TF_up = td_p1_TF.groupby('our rating').apply(lambda x: resample(x,␣
↪random_state=1, replace=True, n_samples=n_samples))

true_count_up = (td_p1_TF_up['our rating'] == 'true').
↪value_counts(normalize=False)[True]
false_count_up = (td_p1_TF_up['our rating'] == 'false').
↪value_counts(normalize=False)[True]
print(true_count_up)
print(false_count_up)
```

```
578
578
```

[232]:

```
# Up and Down sampling
# Categorie B

n_samples = count_labels.max().iloc[0] - int((count_labels.max().iloc[0] -␣
↪count_labels.min().iloc[0])/2)
td_p1_TF_balanced = td_p1_TF.groupby('our rating').apply(lambda x: resample(x,␣
↪random_state=1, replace=True, n_samples=n_samples))

true_count_balanced = (td_p1_TF_balanced['our rating'] == 'true').
↪value_counts(normalize=False)[True]
false_count_balanced = (td_p1_TF_balanced['our rating'] == 'false').
↪value_counts(normalize=False)[True]
print(true_count_balanced)
print(false_count_balanced)
```

```
395
395
```

[233]:

```
# Train with upsampling

X_traincv1_B_up= td_p1_TF_up.text
y_traincv1_B_up = td_p1_TF_up['our rating']
X_testcv1_B = testd_preprocessed1.loc[((testd_preprocessed1['our rating'] ==␣
↪'true' ) | (testd_preprocessed1['our rating'] == 'false'))].text
y_testcv1_B = testd_preprocessed1.loc[((testd_preprocessed1['our rating'] ==␣
↪'true' ) | (testd_preprocessed1['our rating'] == 'false'))]['our rating']

X_traincv1_B_up = cv.fit_transform(X_traincv1_B_up)
X_testcv1_B = cv.transform(X_testcv1_B)

# NB
model = MultinomialNB(alpha=0, force_alpha=True) # no smoothing

model.fit(X_traincv1_B_up, y_traincv1_B_up)
```

```
y_pred_train = model.predict(X_traincv1_B_up)
y_pred_test = model.predict(X_testcv1_B)

print('Accuracy on training data =', accuracy_score(y_traincv1_B_up,␣
↪y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_B, y_pred_test))
print('')
print(metrics.classification_report(y_testcv1_B, y_pred_test))
```

```
Accuracy on training data = 0.9974048442906575
Accuracy on testing data = 0.6019047619047619

              precision    recall  f1-score   support

       false       0.60      0.99      0.75       315
        true       0.57      0.02      0.04       210

    accuracy                           0.60       525
   macro avg       0.59      0.50      0.39       525
weighted avg       0.59      0.60      0.46       525


/usr/local/lib/python3.10/dist-packages/sklearn/naive_bayes.py:907:
RuntimeWarning: divide by zero encountered in log
  self.feature_log_prob_ = np.log(smoothed_fc) - np.log(
```

[234]:

```
# Train with downsampling

X_traincv1_B_down= td_p1_TF_down.text
y_traincv1_B_down = td_p1_TF_down['our rating']
X_testcv1_B = testd_preprocessed1.loc[((testd_preprocessed1['our rating'] ==␣
↪'true' ) | (testd_preprocessed1['our rating'] == 'false'))].text
y_testcv1_B = testd_preprocessed1.loc[((testd_preprocessed1['our rating'] ==␣
↪'true' ) | (testd_preprocessed1['our rating'] == 'false'))]['our rating']

X_traincv1_B_down = cv.fit_transform(X_traincv1_B_down)
X_testcv1_B = cv.transform(X_testcv1_B)

# NB
model = MultinomialNB(alpha=0, force_alpha=True) # no smoothing

model.fit(X_traincv1_B_down, y_traincv1_B_down)

y_pred_train = model.predict(X_traincv1_B_down)
y_pred_test = model.predict(X_testcv1_B)
```

```
print('Accuracy on training data =', accuracy_score(y_traincv1_B_down,␣
↪y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_B, y_pred_test))
print('')
print(metrics.classification_report(y_testcv1_B, y_pred_test))
```

```
Accuracy on training data = 0.9976303317535545
Accuracy on testing data = 0.6095238095238096

              precision    recall  f1-score   support

       false       0.61      0.99      0.75       315
        true       0.69      0.04      0.08       210

    accuracy                           0.61       525
   macro avg       0.65      0.52      0.42       525
weighted avg       0.64      0.61      0.48       525


/usr/local/lib/python3.10/dist-packages/sklearn/naive_bayes.py:907:
RuntimeWarning: divide by zero encountered in log
  self.feature_log_prob_ = np.log(smoothed_fc) - np.log(
```

[243]:

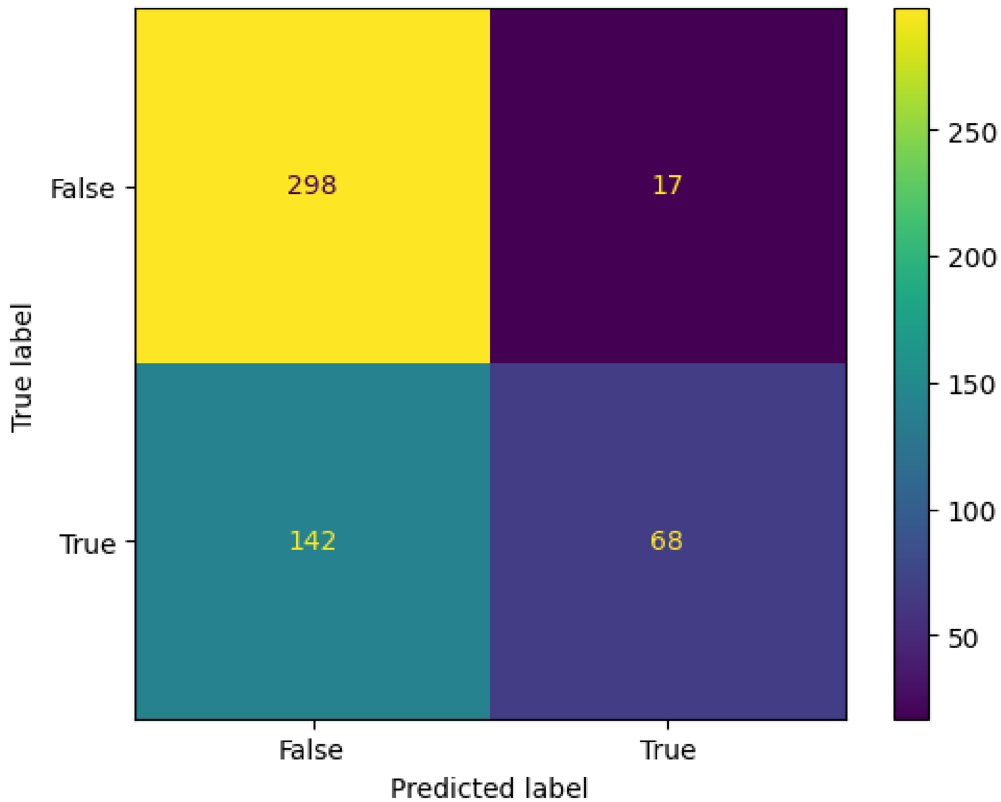
```
# Train with up+downsampling

X_traincv1_B_balanced = td_p1_TF_balanced.text
y_traincv1_B_balanced = td_p1_TF_balanced['our rating']
X_testcv1_B = testd_preprocessed1.loc[((testd_preprocessed1['our rating'] ==␣
↪'true' ) | (testd_preprocessed1['our rating'] == 'false'))].text
y_testcv1_B = testd_preprocessed1.loc[((testd_preprocessed1['our rating'] ==␣
↪'true' ) | (testd_preprocessed1['our rating'] == 'false'))]['our rating']

X_traincv1_B_balanced = cv.fit_transform(X_traincv1_B_balanced)
X_testcv1_B = cv.transform(X_testcv1_B)

# NB
model = MultinomialNB(alpha=0, force_alpha=True) # no smoothing

model.fit(X_traincv1_B_balanced, y_traincv1_B_balanced)

y_pred_train = model.predict(X_traincv1_B_balanced)
y_pred_test = model.predict(X_testcv1_B)

print('Accuracy on training data =', accuracy_score(y_traincv1_B_balanced,␣
↪y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_B, y_pred_test))
print('')
```

```
print(metrics.classification_report(y_testcv1_B, y_pred_test))
```

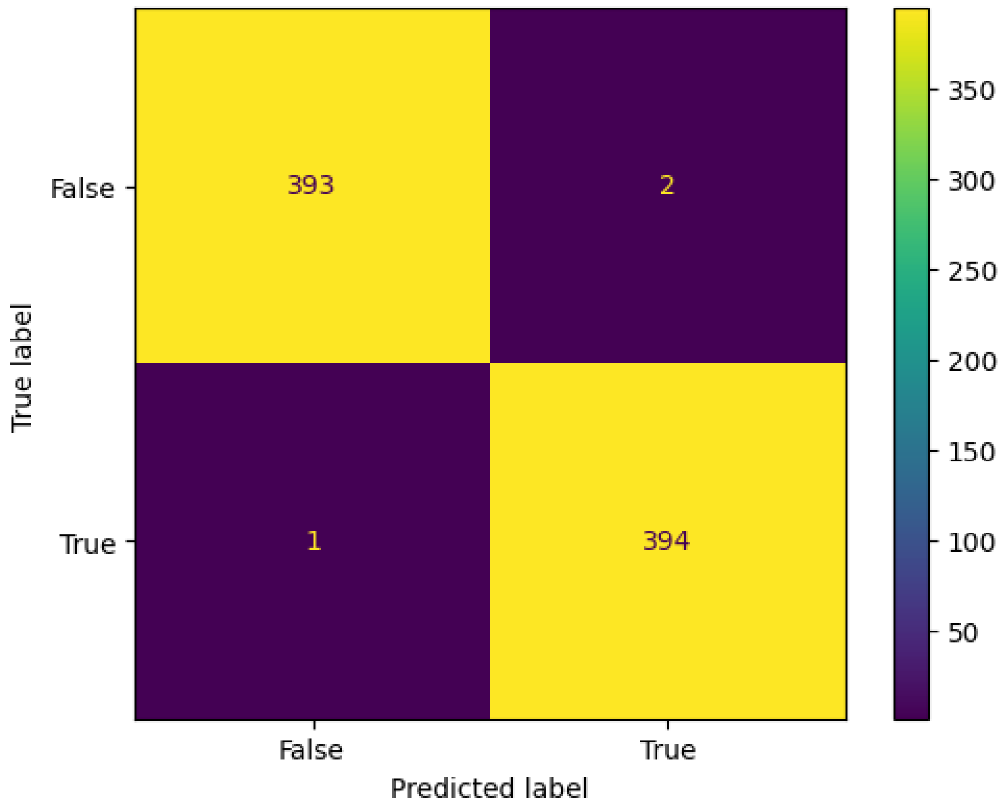
```
Accuracy on training data = 0.9987341772151899
Accuracy on testing data = 0.6019047619047619

              precision    recall  f1-score   support

       false       0.60      0.99      0.75       315
        true       0.57      0.02      0.04       210

    accuracy                           0.60       525
   macro avg       0.59      0.50      0.39       525
weighted avg       0.59      0.60      0.46       525


/usr/local/lib/python3.10/dist-packages/sklearn/naive_bayes.py:907:
RuntimeWarning: divide by zero encountered in log
  self.feature_log_prob_ = np.log(smoothed_fc) - np.log(
```

[236]:

```
confusion_matrix = metrics.confusion_matrix(y_testcv1_B, y_pred_test)

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix =␣
 ↪confusion_matrix, display_labels = [False, True])

cm_display.plot()
plt.show()
```



[237]:
```
confusion_matrix = metrics.confusion_matrix(y_traincv1_B_balanced, y_pred_train)

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix =␣
↪confusion_matrix, display_labels = [False, True])

cm_display.plot()
plt.show()
```



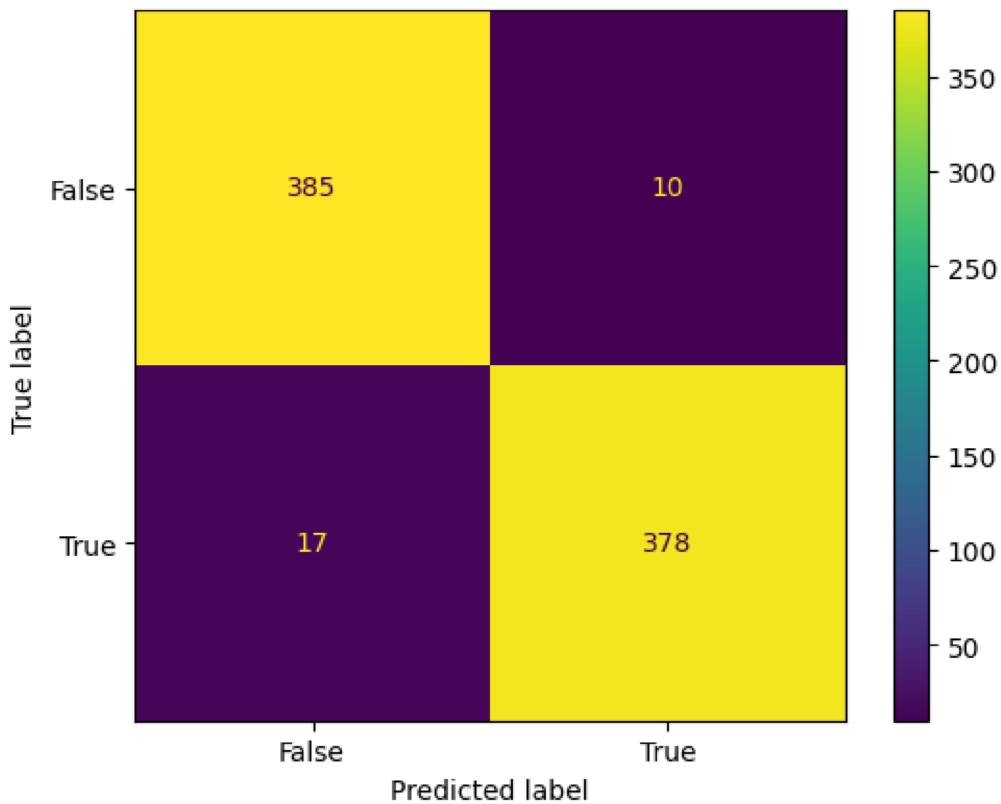
[238]:

```
# LR
model = LogisticRegression(max_iter=1000)

lr = model.fit(X_traincv1_B_balanced, y_traincv1_B_balanced)

y_pred_train = lr.predict(X_traincv1_B_balanced)
y_pred_test = lr.predict(X_testcv1_B)


print('Accuracy on training data =', accuracy_score(y_traincv1_B_balanced,␣
 ↪y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_B, y_pred_test))
print('')
print(metrics.classification_report(y_testcv1_B, y_pred_test))
```

```
Accuracy on training data = 0.9658227848101266
Accuracy on testing data = 0.6685714285714286

              precision    recall  f1-score   support

       false       0.66      0.92      0.77       315
```

```
        true       0.71      0.29      0.41       210

    accuracy                           0.67       525
   macro avg       0.69      0.60      0.59       525
weighted avg       0.68      0.67      0.63       525
```

[239]:
```
confusion_matrix = metrics.confusion_matrix(y_traincv1_B_balanced, y_pred_train)

cm_display = metrics.ConfusionMatrixDisplay(confusion_matrix =␣
 ↪confusion_matrix, display_labels = [False, True])

cm_display.plot()
plt.show()
```



[240]:
```
# Random forest
n_estimators = 1000
min_samples_split = 10
min_samples_leaf = 1
max_depth = None
bootstrap = False
```

```
best_model = RandomForestClassifier(n_estimators=n_estimators,␣
 ↪min_samples_split=min_samples_split, min_samples_leaf=min_samples_leaf,␣
 ↪max_depth=max_depth, bootstrap=bootstrap)

y_pred_train = lr.predict(X_traincv1_B_balanced)
y_pred_test = lr.predict(X_testcv1_B)


print('Accuracy on training data =', accuracy_score(y_traincv1_B_balanced,␣
 ↪y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_B, y_pred_test))
print('')
print(metrics.classification_report(y_testcv1_B, y_pred_test))
```

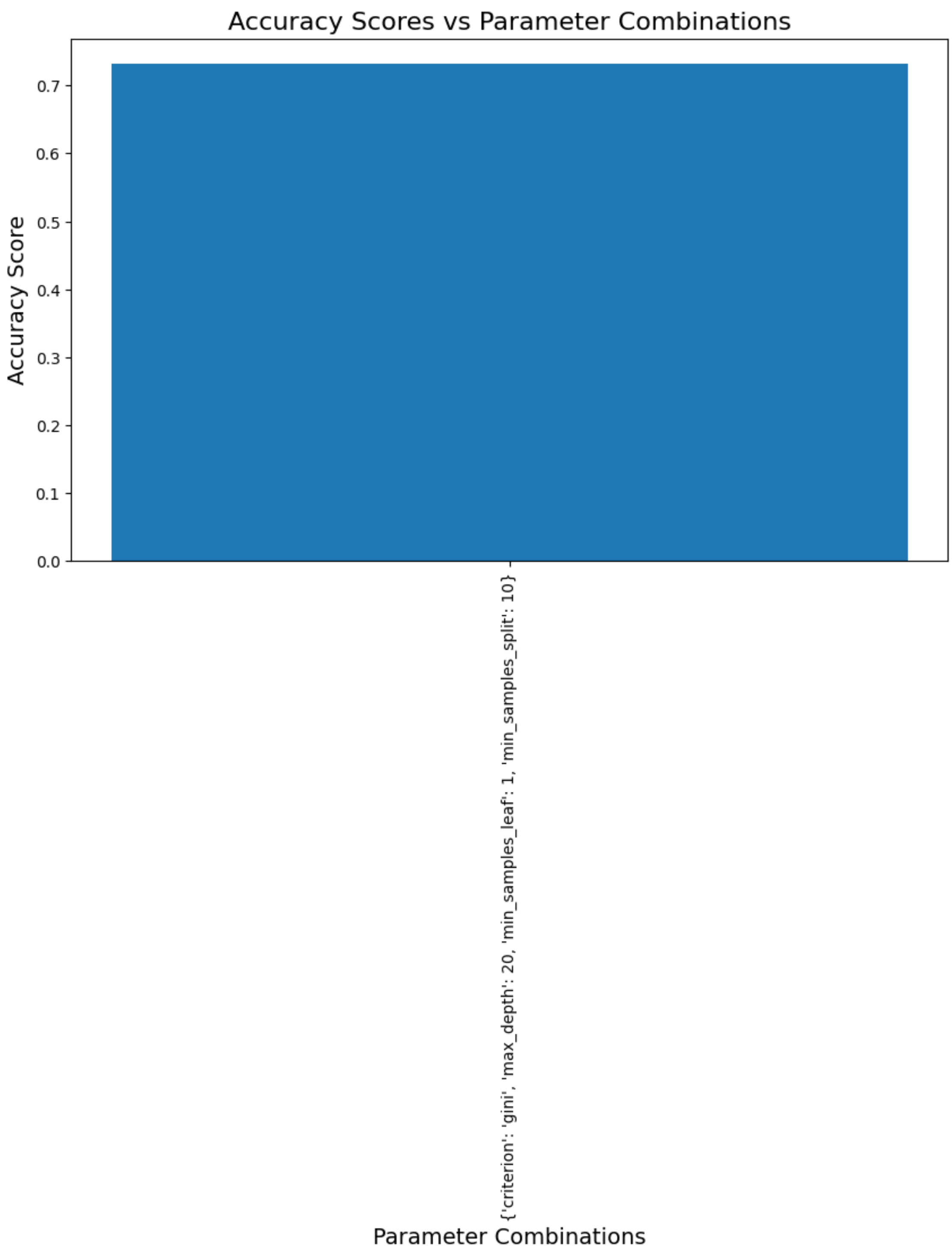
```
Accuracy on training data = 0.9658227848101266
Accuracy on testing data = 0.6685714285714286

              precision    recall  f1-score   support

       false       0.66      0.92      0.77       315
        true       0.71      0.29      0.41       210

    accuracy                           0.67       525
   macro avg       0.69      0.60      0.59       525
weighted avg       0.68      0.67      0.63       525
```

[241]:
```
# a la recherche des meilleurs paramètres pour decision tree

grid_param = {
'max_depth': [7, 10, 20, 50],
'min_samples_split': [10, 20],
'criterion': ['gini', 'entropy'],
'min_samples_leaf': [1,5,10]
}

# Get the accuracy scores for all parameter combinations
scores = gd_sr.cv_results_['mean_test_score']

# Print the best parameters and the corresponding score
print("Best parameters:", gd_sr.best_params_)
print("Best score:", gd_sr.best_score_)

# Create a plot of the accuracy scores vs the different parameter combinations
fig, ax = plt.subplots(figsize=(10, 6))
ax.set_title("Accuracy Scores vs Parameter Combinations", fontsize=16)
ax.set_xlabel("Parameter Combinations", fontsize=14)
```

```
ax.set_ylabel("Accuracy Score", fontsize=14)
ax.bar(range(len(scores)), scores)
ax.set_xticks(range(len(scores)))
ax.set_xticklabels([str(params) for params in gd_sr.cv_results_['params']],␣
 ↪rotation=90)
plt.tight_layout()
plt.show()
```

```
Best parameters: {'criterion': 'gini', 'max_depth': 20, 'min_samples_leaf': 1,
'min_samples_split': 10}
Best score: 0.7325868224602402
```

```
<ipython-input-241-66f5368248e9>:25: UserWarning: Tight layout not applied. The
bottom and top margins cannot be made large enough to accommodate all axes
decorations.
  plt.tight_layout()
```



[242]:
```
# decision tree, up + down sampling, best parameters
grid_param = {'criterion': ['gini'], 'max_depth': [20], 'min_samples_leaf':␣
↪[1], 'min_samples_split': [10]}
```

```
gd_sr = GridSearchCV(estimator=DecisionTreeClassifier(),
param_grid=grid_param,
scoring='accuracy',
cv=10,
n_jobs=-1,
return_train_score=True)

dt = gd_sr.fit(X_traincv1_B_balanced, y_traincv1_B_balanced)

y_pred_train = dt.predict(X_traincv1_B_balanced)
y_pred_test = dt.predict(X_testcv1_B)

print('Accuracy on training data =', accuracy_score(y_traincv1_B_balanced,␣
 ↪y_pred_train))
print('Accuracy on testing data =', accuracy_score(y_testcv1_B, y_pred_test))
print('')
```

```
Accuracy on training data = 0.9886075949367089
Accuracy on testing data = 0.5923809523809523
```