Projet Apprentissage supervisé - JELTI _ BAYRI _ ET-TALI (AMSD)

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1 1. Données Crédits bancaires

1.1 Importations

[ ]:
```
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
from numpy import mean
from numpy import std
from pandas import read_csv
from matplotlib import pyplot
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import OneHotEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.metrics import fbeta_score
from sklearn.metrics import make_scorer
from sklearn.linear_model import LogisticRegression
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.gaussian_process import GaussianProcessClassifier
from sklearn.svm import SVC
from collections import Counter
```

1.2 *Une étude exploratoire préliminaire*

1.2.1 *Lecture et pré-traitement des données*

[ ]:
```
credit_df = pd.read_csv('https://raw.githubusercontent.com/jbrownlee/Datasets/
 ↪master/german.csv', header = None)
credit_df
```

[ ]:
```
       0    1    2    3     4    5    6  …     14  15    16  17    18    19  20
0    A11    6  A34  A43  1169  A65  A75  …   A152   2  A173   1  A192  A201   1
1    A12   48  A32  A43  5951  A61  A73  …   A152   1  A173   1  A191  A201   2
2    A14   12  A34  A46  2096  A61  A74  …   A152   1  A172   2  A191  A201   1
3    A11   42  A32  A42  7882  A61  A74  …   A153   1  A173   2  A191  A201   1
4    A11   24  A33  A40  4870  A61  A73  …   A153   2  A173   2  A191  A201   2
..   …  ..   …   …    …  …   …   …    …  ..   …  ..    …    …  ..
995  A14   12  A32  A42  1736  A61  A74  …   A152   1  A172   1  A191  A201   1
996  A11   30  A32  A41  3857  A61  A73  …   A152   1  A174   1  A192  A201   1
997  A14   12  A32  A43   804  A61  A75  …   A152   1  A173   1  A191  A201   1
998  A11   45  A32  A43  1845  A61  A73  …   A153   1  A173   1  A192  A201   2
999  A12   45  A34  A41  4576  A62  A71  …   A152   1  A173   1  A191  A201   1

[1000 rows x 21 columns]
```

Nous pouvons voir que les colonnes catégorielles sont encodées avec un format Axxx, où "x" sont des entiers pour les différents labels.

Nous pouvons également constater que les variables numériques ont des échelles différentes. Cela suggère que la mise à l'échelle des colonnes de nombres entiers sera nécessaire pour les algorithmes qui sont sensibles à l'échelle.

[ ]:
```
print(credit_df.shape)
```

```
(1000, 21)
```

[ ]:
```
target = credit_df.values[:,-1]
counter = Counter(target)
for k,v in counter.items():
        per = v / len(target) * 100
        print('Class=%d, Count=%d, Percentage=%.3f%%' % (k, v, per))
```

```
Class=1, Count=700, Percentage=70.000%
Class=2, Count=300, Percentage=30.000%
```

Suite à la distribution des classes, on peut dire que la classe = 1 est majoritaire.

[ ]:
```
num_var = credit_df.select_dtypes(include=['int64', 'float64']).columns
num_credit_df = credit_df[num_var]
num_credit_df
```

[ ]:
```
      1     4   7   10  12  15  17  20
0     6  1169   4   4   67   2   1   1
1    48  5951   2   2   22   1   1   2
2    12  2096   2   3   49   1   2   1
3    42  7882   2   4   45   1   2   1
4    24  4870   3   4   53   2   2   2
..   ..   …    ..  ..  ..  ..  ..  ..
995  12  1736   3   4   31   1   1   1
996  30  3857   4   4   40   1   1   1
997  12   804   4   4   38   1   1   1
998  45  1845   4   4   23   1   1   2
999  45  4576   3   4   27   1   1   1

[1000 rows x 8 columns]
```

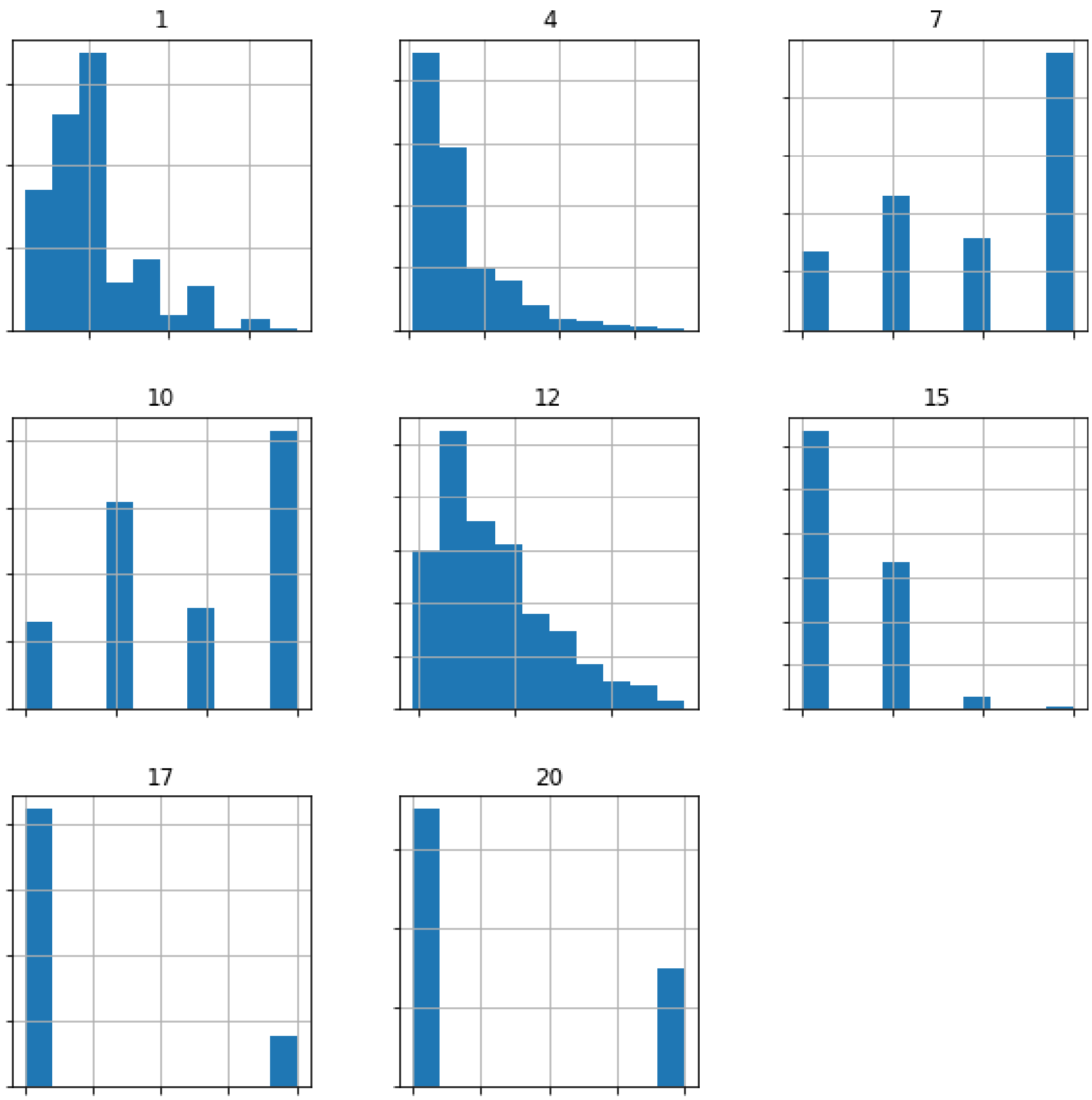
Nous avons sélectionné les colonnes contenant des variables numériques. \ Nous avons 7 colonnes plus la colonne (index = 12) des labels.

[ ]:
```
print(num_credit_df.isnull().any())
print(num_credit_df.isnull().sum().sum())
```

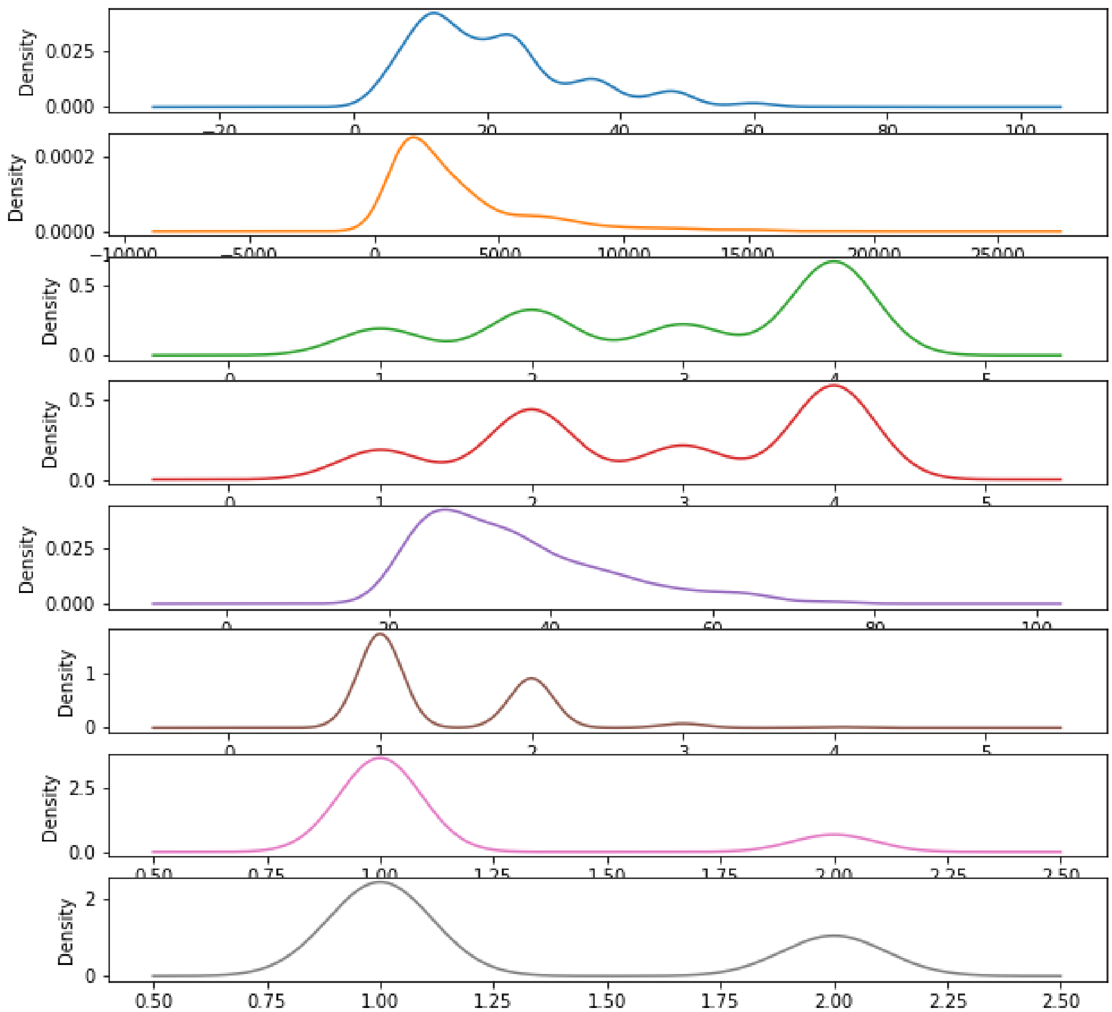
```
1     False
4     False
7     False
10    False
12    False
15    False
17    False
20    False
dtype: bool
0
```

1.2.2 *Visualisation des données*

[ ]:
```
import matplotlib as mpl
mpl.rcParams['figure.figsize'] = 10, 10
ax = num_credit_df.hist()
for axis in ax.flatten():
        axis.set_xticklabels([])
        axis.set_yticklabels([])
pyplot.show()
```



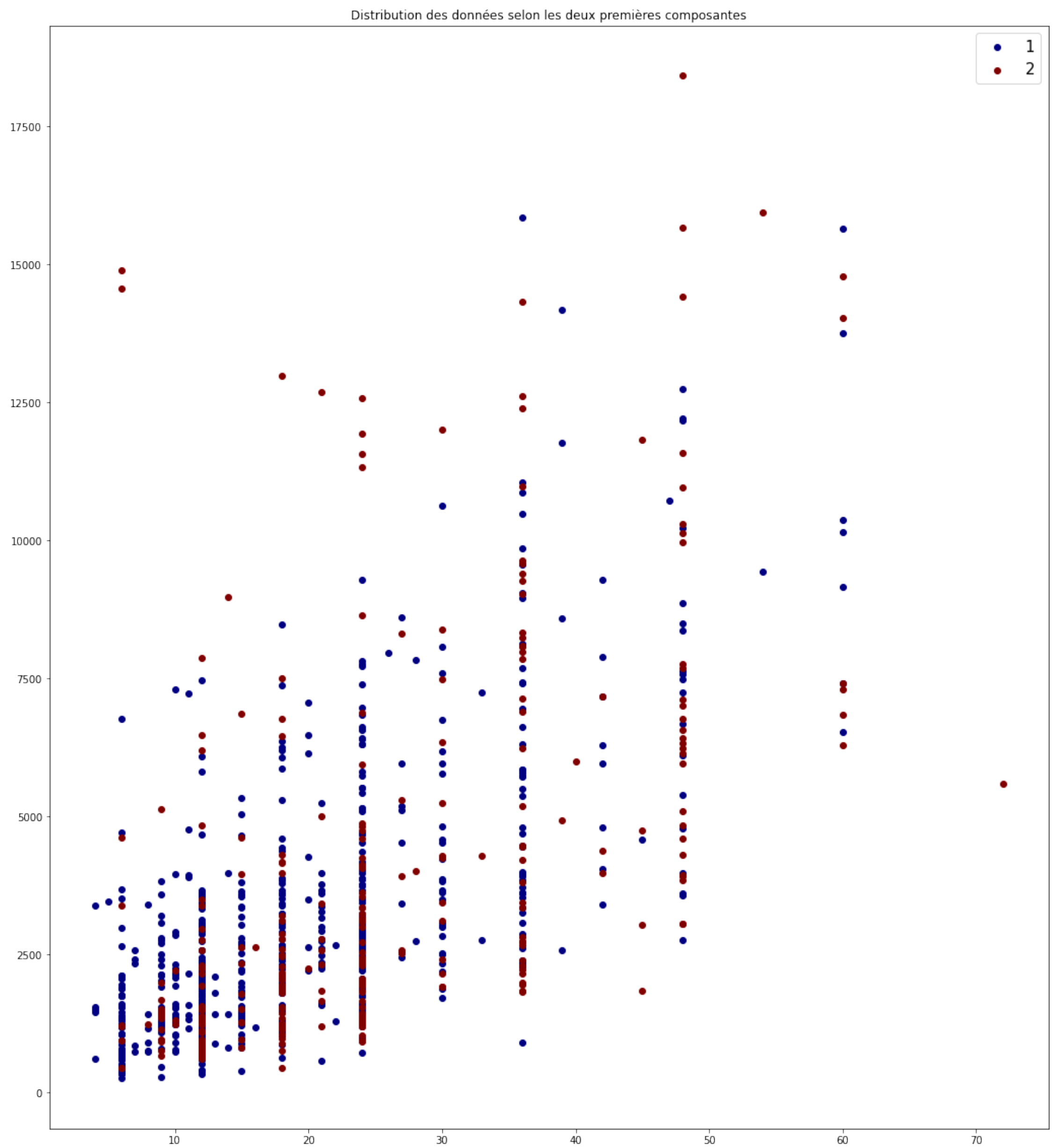
[ ]:
```
credit_df.plot(kind='density', subplots=True, sharex=False, legend=False)
pyplot.show()
```



[ ]:
```
y = num_credit_df[20]
X = num_credit_df.drop([20], axis='columns')
x1=X.iloc[:,0]
x2=X.iloc[:,1]
classes = y
unique = np.unique(classes)
colors = [plt.cm.jet(i/float(len(unique)-1)) for i in range(len(unique))]
fig1=plt.figure(figsize=(60,20))
ax1 = fig1.add_subplot(131)
for i, u in enumerate(unique):
    xi = [x1[j] for j  in range(len(x1)) if classes[j] == u]
    yi = [x2[j] for j  in range(len(x2)) if classes[j] == u]
    ax1.scatter(xi, yi, c=colors[i], label=str(u))
plt.legend(fontsize=15)
plt.title("Distribution des données selon les deux premières composantes")
```

```
plt.show()
```

```
*c* argument looks like a single numeric RGB or RGBA sequence, which should be
avoided as value-mapping will have precedence in case its length matches with
*x* & *y*.  Please use the *color* keyword-argument or provide a 2-D array with
a single row if you intend to specify the same RGB or RGBA value for all points.
*c* argument looks like a single numeric RGB or RGBA sequence, which should be
avoided as value-mapping will have precedence in case its length matches with
*x* & *y*.  Please use the *color* keyword-argument or provide a 2-D array with
a single row if you intend to specify the same RGB or RGBA value for all points.
```



1.3 *Traitement des données*

Nous divisons les données en entrées et en sorties.Ensuite nous appliquons l'encodage one-hot sur toutes les variables d'entrée qui sont catégoriques.

```
[ ]: last_ix = len(credit_df.columns) - 1
     X, y = credit_df.drop(last_ix, axis=1), credit_df[last_ix]
     ct_credit_df = X.select_dtypes(include=['object', 'bool']).columns
     ct_data = ColumnTransformer([('o',OneHotEncoder(),ct_credit_df)],␣
      ↪remainder='passthrough')
     X_transformer = ct_data.fit_transform(X)
     X_transformer
```

```
[ ]: array([[ 1.,  0.,  0., …, 67.,  2.,  1.],
            [ 0.,  1.,  0., …, 22.,  1.,  1.],
            [ 0.,  0.,  0., …, 49.,  1.,  2.],
            …,
            [ 0.,  0.,  0., …, 38.,  1.,  1.],
            [ 1.,  0.,  0., …, 23.,  1.,  1.],
            [ 0.,  1.,  0., …, 27.,  1.,  1.]])
```

```
[ ]: # Encodage de la variable de la sortie en classe 0 et 1
     y = LabelEncoder().fit_transform(y)
     y[:10]
```

```
[ ]: array([0, 1, 0, 0, 1, 0, 0, 0, 0, 1])
```

1.4 *Evaluate Algorithms*

```
[ ]: def f2(y_true, y_pred):
             return fbeta_score(y_true, y_pred, beta=2)
```

```
[ ]: def get_models():
       models = []
       models.append(('LR', LogisticRegression()))
       models.append(('LDA', LinearDiscriminantAnalysis()))
       models.append(('KNN', KNeighborsClassifier()))
       models.append(('CART', DecisionTreeClassifier()))
       models.append(('NB', GaussianNB()))
       models.append(('SVM', SVC()))
       return models

     def evaluate_model(X, y, model):
             cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
             metric = make_scorer(f2)
             scores = cross_val_score(model, X, y, scoring=metric, cv=cv, n_jobs=-1)
```

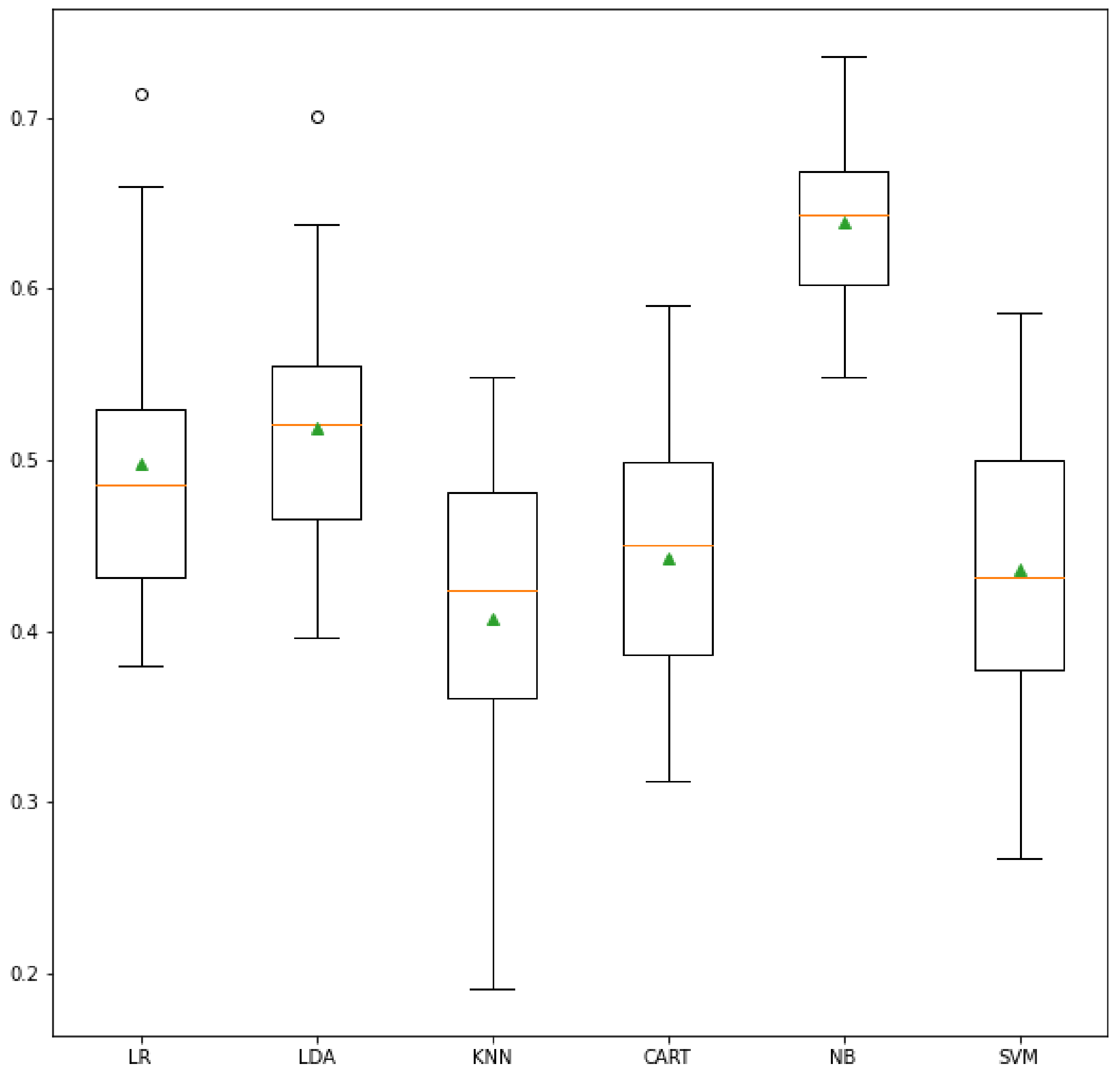
```
        return scores
models= get_models()
```

[ ]:
```
results = list()
names = []
cat_ix = X.select_dtypes(include=['object', 'bool']).columns
num_ix = X.select_dtypes(include=['int64', 'float64']).columns
for name, algo in models:
  # one hot encode categorical, normalize numerical
  ct = ColumnTransformer([('c',OneHotEncoder(),cat_ix),␣
 ↪('n',MinMaxScaler(),num_ix)])
  # wrap the model i a pipeline
  pipeline = Pipeline(steps=[('t',ct),('m',algo)])
  # evaluate the model and store results
  scores = evaluate_model(X.values, y, pipeline)
  results.append(scores)
  names.append(name)
  print('>%s %.3f (%.3f)' % (name, mean(scores), std(scores)))
```

```
>LR 0.498 (0.076)
>LDA 0.519 (0.072)
>KNN 0.407 (0.096)
>CART 0.442 (0.077)
>NB 0.639 (0.049)
>SVM 0.436 (0.077)
```

On remarque que le Bayesien Naïf donne le meilleur résultat.

[ ]:
```
pyplot.boxplot(results, labels=names, showmeans=True)
pyplot.show()
```



2 *Pubmed data*

2.0.1 Importations

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, roc_curve, accuracy_score,␣
 ↪precision_score, recall_score, f1_score, roc_auc_score
```

```python
from sklearn.model_selection import cross_val_score, GridSearchCV
from sklearn.svm import SVC
import scipy
from scipy.io import loadmat
from imblearn.under_sampling import NeighbourhoodCleaningRule
from imblearn.over_sampling  import RandomOverSampler
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics.cluster import normalized_mutual_info_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
import warnings
warnings.filterwarnings('ignore')
```

2.0.2 *Matrice X*

Analyse exploratoire des données

Lecture des données

[ ]:
```python
pubmed = scipy.io.loadmat('/content/pubmed.mat')
```

[ ]:
```python
pubmed
```

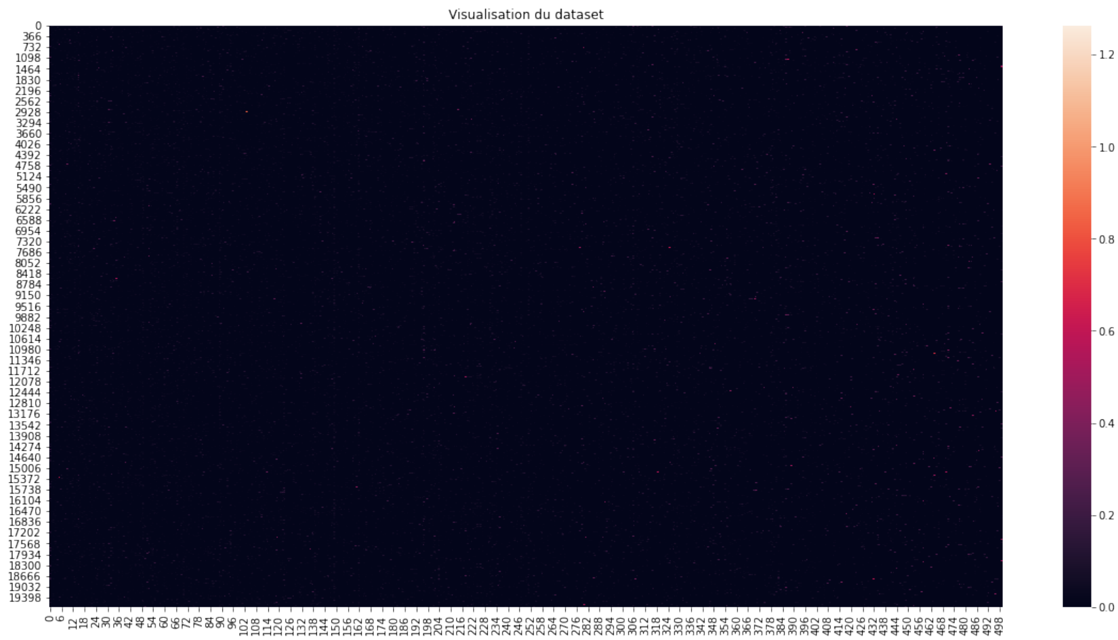
[ ]:
```
{'W': <19717x19717 sparse matrix of type '<class 'numpy.float64'>'
        with 88651 stored elements in Compressed Sparse Column format>,
 '__globals__': [],
 '__header__': b'MATLAB 5.0 MAT-file, Platform: PCWIN64, Created on: Wed Jan 30
19:12:21 2019',
 '__version__': '1.0',
 'fea': array([[0.        , 0.        , 0.        , …, 0.        , 0.        ,
         0.        ],
        [0.        , 0.        , 0.        , …, 0.        , 0.        ,
         0.        ],
        [0.10463634, 0.        , 0.        , …, 0.        , 0.        ,
         0.        ],
        …,
        [0.        , 0.01942665, 0.0079607 , …, 0.        , 0.        ,
         0.        ],
        [0.10782092, 0.        , 0.        , …, 0.        , 0.        ,
         0.        ],
        [0.        , 0.02658384, 0.        , …, 0.        , 0.        ,
         0.        ]]),
 'gnd': array([[2],
```

```
       [2],
       [1],
       ...,
       [3],
       [1],
       [3]], dtype=uint8)}
```

Visualisation des données

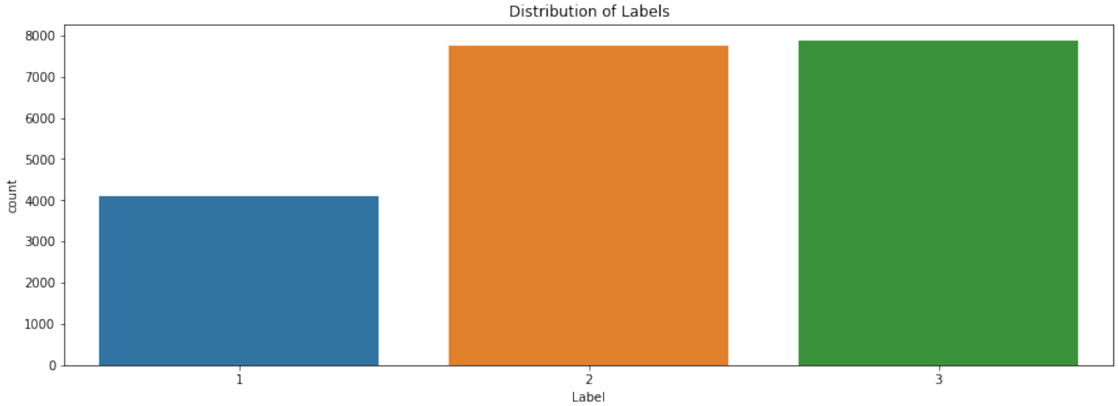
[ ]:
```python
fig, ax = plt.subplots(figsize=(20,10))
ax = sns.heatmap(pubmed["fea"])
ax.set_title("Visualisation du dataset")
```

[ ]:
```
Text(0.5, 1.0, 'Visualisation du dataset')
```



[ ]:
```python
fig, ax = plt.subplots(figsize=(15,5))
ax = sns.countplot(x = pubmed["gnd"].flatten())
ax.set_title('Distribution of Labels')
ax.set_xlabel('Label')
```

[ ]:
```
Text(0.5, 0, 'Label')
```



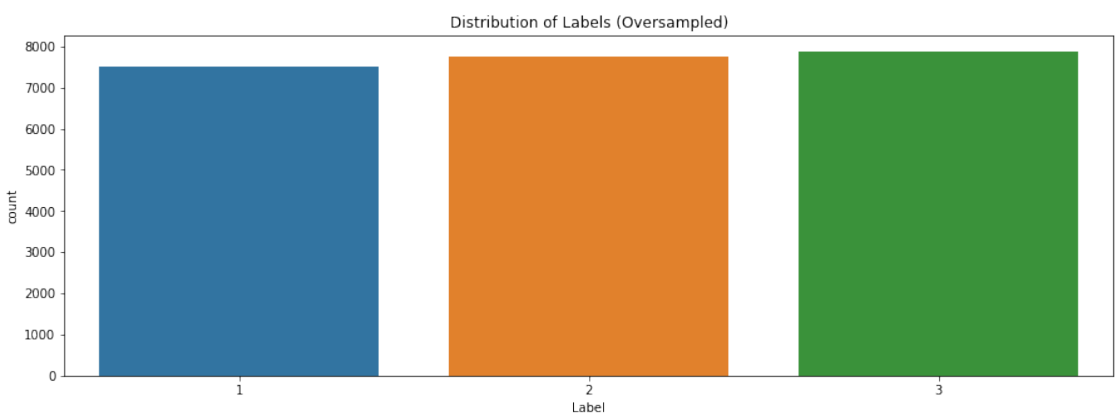
Suite à la visualisation des données, on remarque que les classes sont déséquilibrées.La classe 1 est minoritaire. \ Nous allons donc essayer d'équilibrer ces classes.

Over sampling data Équilibrage des données en utilisant ROS over−sampling tant qu'on a pas beaucoup de data.

[ ]:
```
# Équilibrage des données en utilisant ROS over-sampling
ros = RandomOverSampler(sampling_strategy={1 : 7500})
X_resampled, y_resampled = ros.fit_sample(pubmed["fea"], pubmed["gnd"].
 ↪flatten())
```

[ ]:
```
fig, ax = plt.subplots(figsize=(15,5))
ax = sns.countplot(x = y_resampled)
ax.set_title('Distribution of Labels (Oversampled)')
ax.set_xlabel('Label')
```

[ ]:
```
Text(0.5, 0, 'Label')
```



Nous remarquons qu'après l'application de la méthode ROS over−sampling, nous avons pu équilibrer la data.

Classification

Données train/test sets

```
[ ]: X_train, X_test, Y_train, Y_test = train_test_split(X_resampled, y_resampled,␣
      ↪test_size=0.2)
```

```
[ ]: # Dictionnaire qui nous servira par la suite pour comparer les résultats
     f1_scores = dict()
     acc_scores = dict()
```

Naive Bayes Classifier On a une distribution de données équivalente à celle d'une distribution Multinomiale, donc, on va utiliser la variante MultinomialNB de Naive Bayes.

```
[ ]: clf_nb = MultinomialNB()
```

```
[ ]: clf_nb.fit(X_train, Y_train)
```

```
[ ]: MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)
```

```
[ ]: pred_nb = clf_nb.predict(X_test)
```

```
[ ]: confusion_matrix(Y_test, pred_nb)
```

```
[ ]: array([[1333,   31,   91],
            [ 150, 1346,   88],
            [ 122,  379, 1083]])
```

```
[ ]: acc_nb = accuracy_score(Y_test, pred_nb)
     print("Naive Bayes Accuracy :\n"+str(acc_nb))
     print("Naive Bayes Precision :\n"+str(precision_score(Y_test, pred_nb,␣
      ↪average="macro")))
     print("Naive Bayes Recall :\n"+str(recall_score(Y_test, pred_nb,␣
      ↪average="macro")))
     f1_nb = f1_score(Y_test, pred_nb, average="macro")
     print("Naive Bayes F1-Score :\n"+str(f1_nb))
     f1_scores["Multinomial Naive Bayes Classifier sur X"] = f1_nb
     acc_scores["Multinomial Naive Bayes Classifier sur X"] = acc_nb
```

```
Naive Bayes Accuracy :
0.8137573004542504
Naive Bayes Precision :
0.8184020165237348
```

```
Naive Bayes Recall :
0.8165369329029123
Naive Bayes F1-Score :
0.8127660066214193
```

Random Forests Nous allons utiliser la méthodes de grid search pour trouver les paramètres du modèles

[ ]:
```
#Recherche des paramètres par grid search
def rf_grid_search(X, y):
    feature_mode = ['sqrt', 'log2']
    param_grid_search = {'max_features': feature_mode}

    grid_search = GridSearchCV(RandomForestClassifier(n_jobs=-1),␣
 ↪param_grid_search, scoring='f1_macro', return_train_score=True)
    grid_search.fit(X, y)

    return grid_search.best_params_
```

[ ]:
```
rnd_fr_clf = RandomForestClassifier(max_features = 'sqrt', n_jobs=-1)
rnd_fr_clf.fit(X_train, Y_train)
```

[ ]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='sqrt',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=-1, oob_score=False, random_state=None, verbose=0,
                       warm_start=False)
```

[ ]:
```
rnd_fr_predicted = rnd_fr_clf.predict(X_test)
```

[ ]:
```
acc_rf = accuracy_score(Y_test, rnd_fr_predicted)
print("Random Forests Accuracy :\n"+str(acc_rf))
print("Random Forests Precision :\n"+str(precision_score(Y_test,␣
 ↪rnd_fr_predicted, average="macro")))
print("Random Forests Recall :\n"+str(recall_score(Y_test, rnd_fr_predicted,␣
 ↪average="macro")))
f1_rf = f1_score(Y_test, rnd_fr_predicted, average="macro")
print("Random Forests F1-Score :\n"+str(f1_rf))
f1_scores["Random Forests sur X"] = f1_rf
acc_scores["Random Forests sur X"] = acc_rf
```

```
Random Forests Accuracy :
0.9102314514384598
Random Forests Precision :
```

```
0.9106880033016784
Random Forests Recall :
0.9117354819674407
Random Forests F1-Score :
0.9105803054817301
```

Quadratic Discriminant Analysis

[ ]:
```
clf = QuadraticDiscriminantAnalysis()
clf.fit(X_train, Y_train)
```

[ ]:
```
QuadraticDiscriminantAnalysis(priors=None, reg_param=0.0,
                              store_covariance=False, tol=0.0001)
```

[ ]:
```
y_predicted_qda = clf.predict(X_test)
```

[ ]:
```
acc_qda = accuracy_score(Y_test, y_predicted_qda)
print("QDA Accuracy :\n"+str(acc_qda))
print("QDA Precision :\n"+str(precision_score(Y_test, y_predicted_qda,␣
 ↪average="macro")))
print("QDA Recall :\n"+str(recall_score(Y_test, y_predicted_qda,␣
 ↪average="macro")))
f1_qda = f1_score(Y_test, y_predicted_qda, average="macro")
print("QDA F1-Score :\n"+str(f1_qda))
f1_scores["Quadratic Discriminant Analysis sur X"] = f1_qda
acc_scores["Quadratic Discriminant Analysis sur X"] = acc_qda
```

```
QDA Accuracy :
0.8066190785204412
QDA Precision :
0.8116544027221996
QDA Recall :
0.8101708667430317
QDA F1-Score :
0.8039279951608472
```

Linear Discriminant Analysis

[ ]:
```
clf = LinearDiscriminantAnalysis()
clf.fit(X_train, Y_train)
```

[ ]:
```
LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None,
                           solver='svd', store_covariance=False, tol=0.0001)
```

[ ]:
```
y_predicted_lda = clf.predict(X_test)
```

```
[ ]: acc_lda = accuracy_score(Y_test, y_predicted_lda)
     print("LDA Accuracy :\n"+str(acc_lda))
     print("LDA Precision :\n"+str(precision_score(Y_test, y_predicted_lda,␣
      ↪average="macro")))
     print("LDA Recall :\n"+str(recall_score(Y_test, y_predicted_lda,␣
      ↪average="macro")))
     f1_lda = f1_score(Y_test, y_predicted_lda, average="macro")
     print("LDA F1-Score :\n"+str(f1_lda))
     f1_scores["Linear Discriminant Analysis sur X"] = f1_lda
     acc_scores["Linear Discriminant Analysis sur X"] = acc_lda
```

```
LDA Accuracy :
0.8680510491023146
LDA Precision :
0.8684090122092418
LDA Recall :
0.8694314276788503
LDA F1-Score :
0.8683557010897127
```

2.1 *Combinaison des informations W et X*

```
[ ]: D_1 = scipy.sparse.csc_matrix(np.diag(1/np.squeeze(np.asarray(pubmed["W"].
      ↪sum(axis=1)))))
```

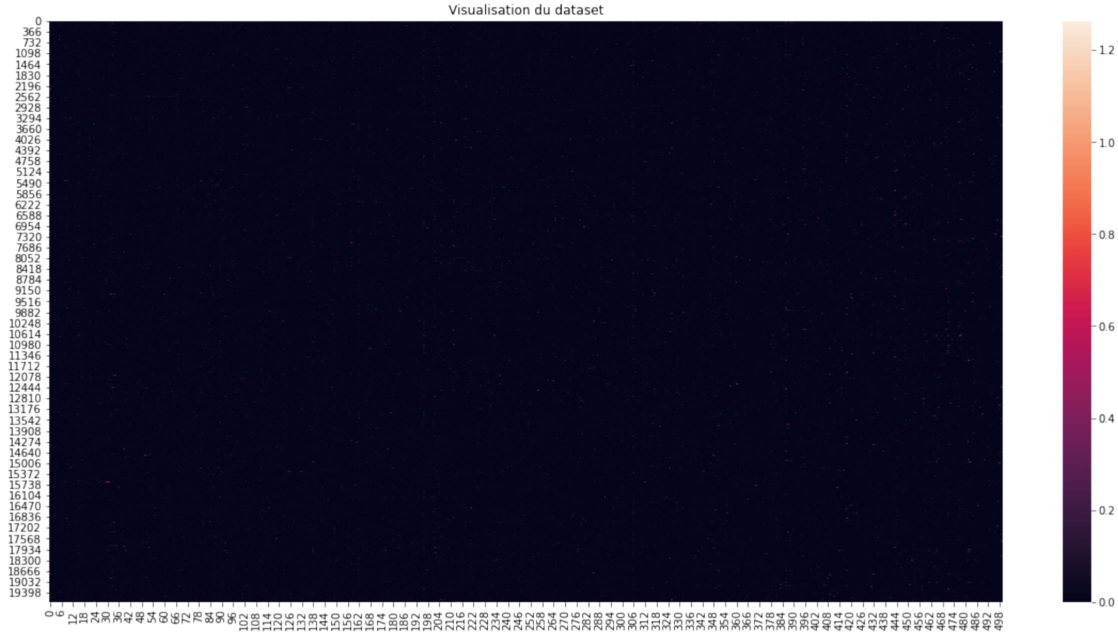
```
[ ]: M = (D_1 * pubmed["W"] )* pubmed["fea"]
```

Analyse exploratoire des données

Visualisation des données

```
[ ]: fig, ax = plt.subplots(figsize=(20,10))
     ax = sns.heatmap(M)
     ax.set_title("Visualisation du dataset")
```

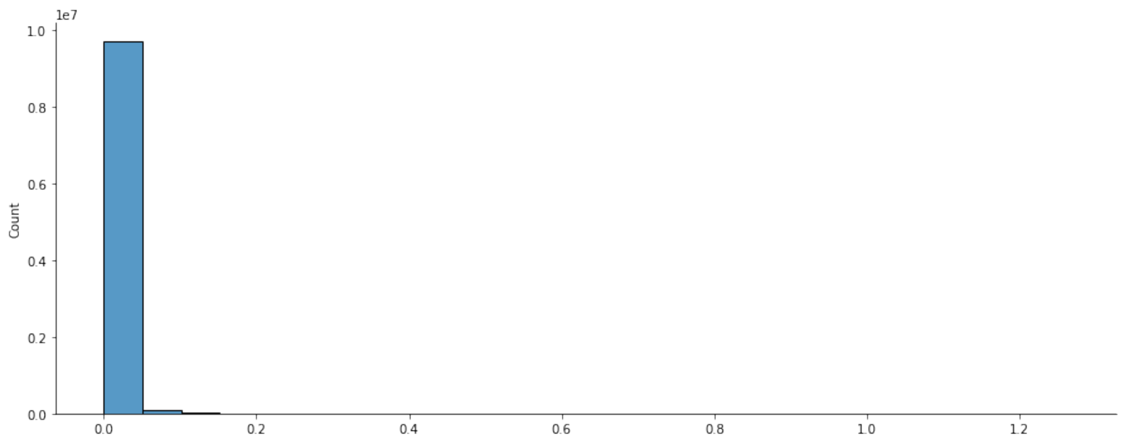
```
[ ]: Text(0.5, 1.0, 'Visualisation du dataset')
```



Distribution des valeurs du dataset

[ ]:
```
sns.displot(M.flatten(), aspect=2.5)
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x7fe5a37e8e50>

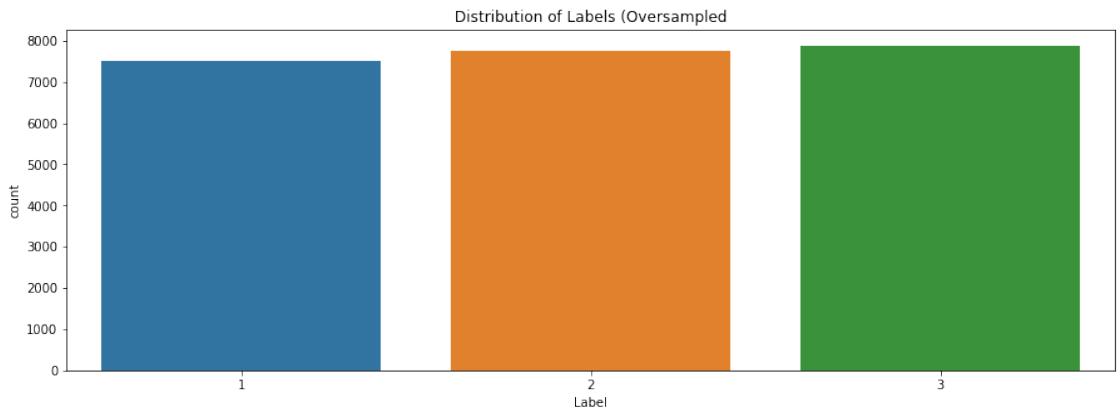


Over sampling data

[ ]:
```
# Équilibrage des données en utilisant ROS over-sampling
ros = RandomOverSampler(sampling_strategy={1 : 7500})
X_resampled, y_resampled = ros.fit_sample(M, pubmed["gnd"].flatten())
```

[ ]:
```
fig, ax = plt.subplots(figsize=(15,5))
ax = sns.countplot(x = y_resampled)
ax.set_title('Distribution of Labels (Oversampled')
ax.set_xlabel('Label')
```

[ ]:
```
Text(0.5, 0, 'Label')
```



Classification

Données train/test sets

[ ]:
```
X_train, X_test, Y_train, Y_test = train_test_split(M, pubmed["gnd"].flatten(),␣
↪test_size=0.2)
```

Naive Bayes Classifier On a une distribution de données équivalente à celle d'une distribution Multinomiale, donc, on va utiliser la variante MultinomialNB de Naive Bayes.

[ ]:
```
clf_nb = MultinomialNB()
```

[ ]:
```
clf_nb.fit(X_train, Y_train)
```

[ ]:
```
MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)
```

[ ]:
```
pred_nb = clf_nb.predict(X_test)
```

[ ]:
```
confusion_matrix(Y_test, pred_nb)
```

[ ]:
```
array([[ 477,  142,  208],
       [  76, 1377,  136],
       [  47,  384, 1097]])
```

[ ]:
```
acc_nb = accuracy_score(Y_test, pred_nb)
print("Naive Bayes Accuracy :\n"+str(acc_nb))
print("Naive Bayes Precision :\n"+str(precision_score(Y_test, pred_nb,␣
↪average="macro")))
print("Naive Bayes Recall :\n"+str(recall_score(Y_test, pred_nb,␣
↪average="macro")))
f1_nb = f1_score(Y_test, pred_nb, average="macro")
print("Naive Bayes F1-Score :\n"+str(f1_nb))
f1_scores["Multinomial Naive Bayes Classifier sur M"] = f1_nb
acc_scores["Multinomial Naive Bayes Classifier sur M"] = acc_nb
```

```
Naive Bayes Accuracy :
0.7482251521298174
Naive Bayes Precision :
0.7599570719327592
Naive Bayes Recall :
0.7204327495471702
Naive Bayes F1-Score :
0.7320548442305772
```

Random Forests

[ ]:
```
#print(rf_grid_search(X_train, Y_train))

# Best parameters : max_features = 'sqrt'
```

[ ]:
```
rnd_fr_clf = RandomForestClassifier(max_features = 'sqrt', n_jobs=-1)
rnd_fr_clf.fit(X_train, Y_train)
```

[ ]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='sqrt',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=-1, oob_score=False, random_state=None, verbose=0,
                       warm_start=False)
```

[ ]:
```
rnd_fr_predicted = rnd_fr_clf.predict(X_test)
```

[ ]:
```
acc_rf = accuracy_score(Y_test, rnd_fr_predicted)
print("Random Forests Accuracy :\n"+str(acc_rf))
print("Random Forests Precision :\n"+str(precision_score(Y_test,␣
↪rnd_fr_predicted, average="macro")))
print("Random Forests Recall :\n"+str(recall_score(Y_test, rnd_fr_predicted,␣
↪average="macro")))
f1_rf = f1_score(Y_test, rnd_fr_predicted, average="macro")
```

```
print("Random Forests F1-Score :\n"+str(f1_rf))
f1_scores["Random Forests sur M"] = f1_rf
acc_scores["Random Forests sur M"] = acc_rf
```

```
Random Forests Accuracy :
0.8258113590263692
Random Forests Precision :
0.8176121193265441
Random Forests Recall :
0.8143605411718884
Random Forests F1-Score :
0.8159006545401937
```

Quadratic Discriminant Analysis

[ ]:
```
clf = QuadraticDiscriminantAnalysis()
clf.fit(X_train, Y_train)
```

[ ]:
```
QuadraticDiscriminantAnalysis(priors=None, reg_param=0.0,
                              store_covariance=False, tol=0.0001)
```

[ ]:
```
#Prediction du test set
y_predicted_qda = clf.predict(X_test)
```

[ ]:
```
acc_qda = accuracy_score(Y_test, y_predicted_qda)
print("QDA Accuracy :\n"+str(acc_qda))
print("QDA Precision :\n"+str(precision_score(Y_test, y_predicted_qda,␣
 ↪average="macro")))
print("QDA Recall :\n"+str(recall_score(Y_test, y_predicted_qda,␣
 ↪average="macro")))
f1_qda = f1_score(Y_test, y_predicted_qda, average="macro")
print("QDA F1-Score :\n"+str(f1_qda))
f1_scores["Quadratic Discriminant Analysis sur M"] = f1_qda
acc_scores["Quadratic Discriminant Analysis sur M"] = acc_qda
```

```
QDA Accuracy :
0.7857505070993914
QDA Precision :
0.7768312161720132
QDA Recall :
0.7989871141426476
QDA F1-Score :
0.7787191358993703
```

Linear Discriminant Analysis

[ ]:
```
clf = LinearDiscriminantAnalysis()
clf.fit(X_train, Y_train)
```

[ ]:
```
LinearDiscriminantAnalysis(n_components=None, priors=None, shrinkage=None,
                           solver='svd', store_covariance=False, tol=0.0001)
```

[ ]:
```
#Prediction du test set
y_predicted_lda = clf.predict(X_test)
```

[ ]:
```
acc_lda = accuracy_score(Y_test, y_predicted_lda)
print("LDA Accuracy :\n"+str(acc_lda))
print("LDA Precision :\n"+str(precision_score(Y_test, y_predicted_lda,␣
 ↪average="macro")))
print("LDA Recall :\n"+str(recall_score(Y_test, y_predicted_lda,␣
 ↪average="macro")))
f1_lda = f1_score(Y_test, y_predicted_lda, average="macro")
print("LDA F1-Score :\n"+str(f1_lda))
f1_scores["Linear Discriminant Analysis sur M"] = f1_lda
acc_scores["Linear Discriminant Analysis sur M"] = acc_lda
```

```
LDA Accuracy :
0.8237829614604463
LDA Precision :
0.8146257705184768
LDA Recall :
0.8171956244225062
LDA F1-Score :
0.8158119065503385
```

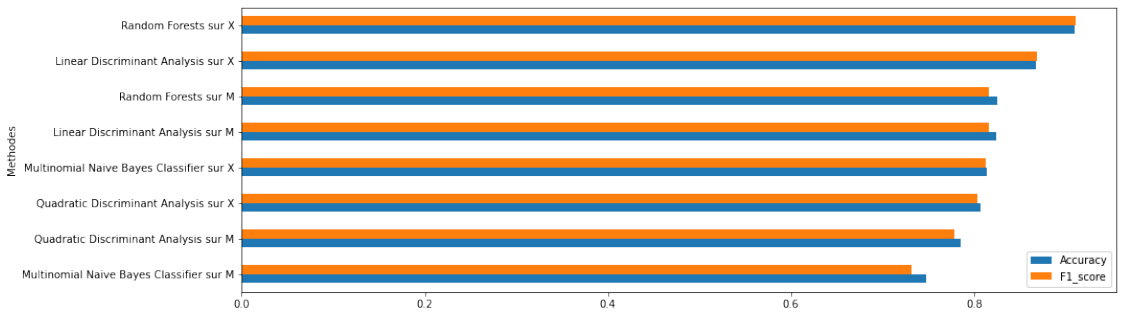
2.1.1 Comparaison des différents modèles

Nous allons faire une comparaison des differentes techniques que nous avons appliquées à l'aide des mesures telles que (Accuracy, NMI et la F-measure).

[ ]:
```
df = pd.DataFrame({"Methodes" : f1_scores.keys(), "Accuracy" : acc_scores.
 ↪values(), "F1_score" : f1_scores.values()}, columns = ["Methodes",␣
 ↪'Accuracy', 'F1_score'])
```

[ ]:
```
df.set_index("Methodes").sort_values("F1_score").plot(kind='barh', legend=True,␣
 ↪figsize=(15,5))
```

[ ]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fe5a05f7dd0>
```



Le meilleur modèle est donc :

En utilisant X ==> **Random Forests**

En utilisant M ==> **Random Forests / Linear Discriminant Analysis**

3 *Cora data*

3.0.1 Importations

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')
!ln -s "/content/drive/My Drive/" mydrive
```

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, roc_curve, precision_score,␣
↪recall_score, f1_score, roc_auc_score
from sklearn.model_selection import cross_val_score, GridSearchCV
from sklearn.svm import SVC
from scipy.io import loadmat
from imblearn.under_sampling import NeighbourhoodCleaningRule
from imblearn.over_sampling  import RandomOverSampler
from sklearn.naive_bayes import BernoulliNB, MultinomialNB
from sklearn.metrics.cluster import normalized_mutual_info_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
```

3.0.2 Analyse exploratoire des données

Lecture des données

[ ]:
```
cora_mat = loadmat('/content/mydrive/app_supp/Donnees_relationnelles/cora.mat')
```

[ ]:
```
cora_mat
```

[ ]:
```
{'W': array([[0, 0, 0, …, 0, 0, 0],
        [0, 0, 1, …, 0, 0, 0],
        [0, 1, 0, …, 0, 0, 0],
        …,
        [0, 0, 0, …, 0, 0, 0],
        [0, 0, 0, …, 0, 0, 1],
        [0, 0, 0, …, 0, 1, 0]], dtype=uint8),
 '__globals__': [],
 '__header__': b'MATLAB 5.0 MAT-file, Platform: PCWIN64, Created on: Fri Jan 18
15:36:27 2019',
 '__version__': '1.0',
 'fea': array([[0, 0, 0, …, 0, 0, 0],
        [0, 0, 0, …, 0, 0, 0],
        [0, 0, 0, …, 0, 0, 0],
        …,
        [0, 0, 0, …, 0, 0, 0],
        [0, 0, 0, …, 0, 0, 0],
        [0, 0, 0, …, 0, 0, 0]], dtype=uint8),
 'gnd': array([[4],
        [5],
        [5],
        …,
        [4],
        [4],
        [4]], dtype=uint8)}
```

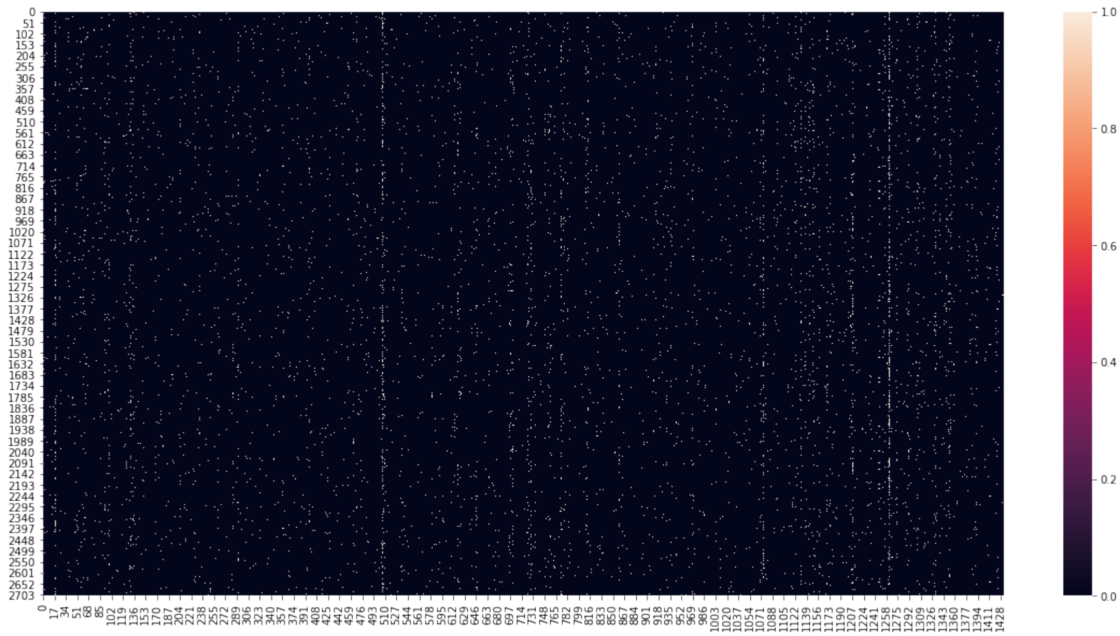
[ ]:
```
X, W, L = cora_mat['fea'], cora_mat['W'], cora_mat['gnd']
```

[ ]:
```
#Pas de NaN Values
np.isnan(X).any()
```

[ ]:
```
False
```

3.0.3 *Visualisation des données*

[ ]:
```
#Heat map
fig, ax = plt.subplots(figsize=(20,10))
ax = sns.heatmap(X)
```

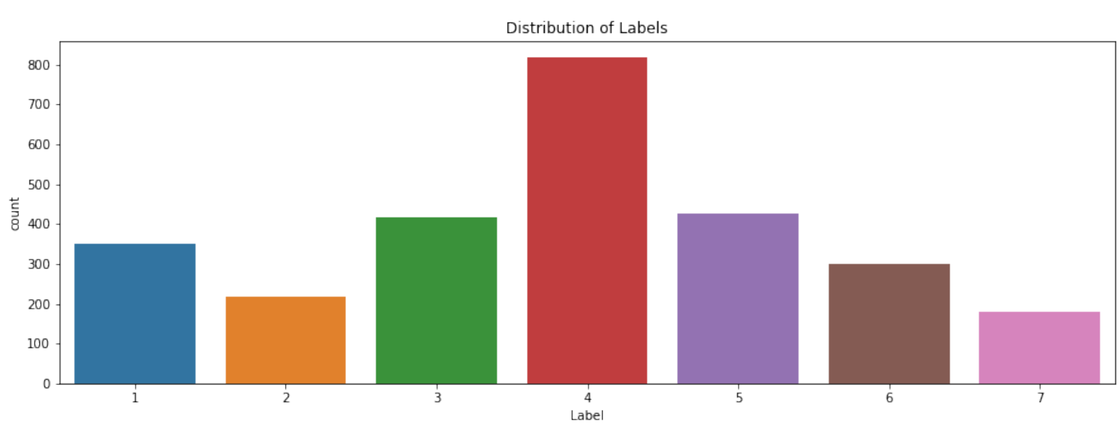


[ ]:
```
#Les valeurs des données => Données binaires
set(W.flatten())
```

[ ]: {0, 1}

[ ]:
```
#Distribution des labels
#Distribution déséquilibrée
fig, ax = plt.subplots(figsize=(15,5))
ax = sns.countplot(x = L.flatten())
ax.set_title('Distribution of Labels')
ax.set_xlabel('Label')
```

[ ]: Text(0.5, 0, 'Label')



Suite à la visualisation des données, on remarque que les classes sont déséquilibrées.La classe 4 est majoritaire. \ Nous allons donc essayer d'équilibrer ces classes.

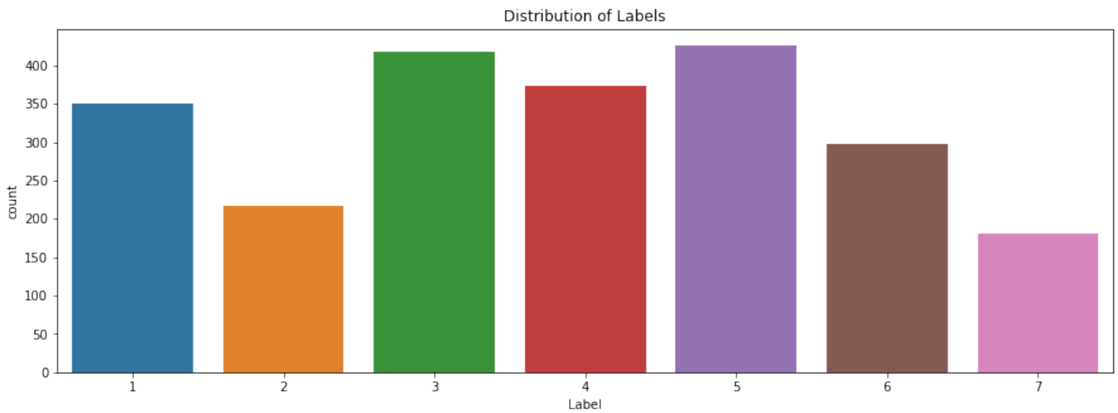
Undersampling/Over sampling data Nous allons faire un sous-échantillonnage de la classe 4.

[ ]:
```
ncl = NeighbourhoodCleaningRule(return_indices=False, sampling_strategy={4 :␣
↪600})
X_resampled, y_resampled = ncl.fit_sample(X, L)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:760:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
ravel().
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
```

[ ]:
```
fig, ax = plt.subplots(figsize=(15,5))
ax = sns.countplot(x = y_resampled.flatten())
ax.set_title('Distribution of Labels')
ax.set_xlabel('Label')
```

[ ]:
```
Text(0.5, 0, 'Label')
```



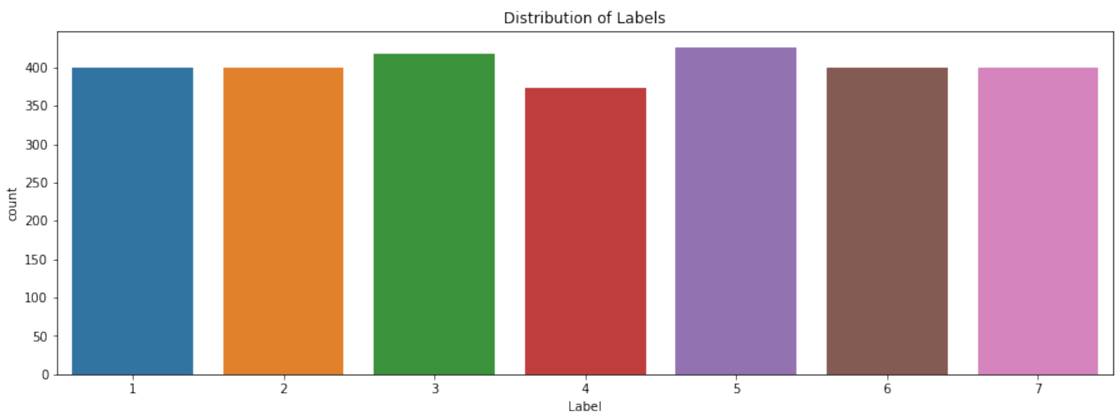
Équilibrage des données en utilisant ROS over−sampling tant qu'on a pas beaucoup de data.

[ ]:
```
ros = RandomOverSampler(sampling_strategy={1 : 400, 2 : 400, 7 : 400, 6 : 400})
X_resampled, y_resampled = ros.fit_sample(X_resampled, y_resampled)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
```

[ ]:
```
fig, ax = plt.subplots(figsize=(15,5))
ax = sns.countplot(x = y_resampled.flatten())
ax.set_title('Distribution of Labels')
ax.set_xlabel('Label')
```

[ ]: Text(0.5, 0, 'Label')



Nous remarquons qu'après l'application de la méthode ROS over−sampling et aussi le Undersampling de la classe 4, nous avons pu équilibrer la data.

3.1 *Classification*

3.1.1 *Séparation des données train/test sets*

[ ]:
```
def split_train_test(data, y_label, test_ratio):
  shuffled_indices = np.random.permutation(len(data))
  test_set_size = int(len(data) * test_ratio)
  test_indices = shuffled_indices[:test_set_size]
  train_indices = shuffled_indices[test_set_size:]
  return data[train_indices], data[test_indices], y_label[train_indices],␣
 ↪y_label[test_indices]
```

[ ]:
```
#Split data into train /test sets
train_set, test_set, y_train, y_test = split_train_test(X_resampled,␣
 ↪y_resampled, 0.2)
```

[ ]:
```
f1_scores = dict()
```

3.1.2 1. Naive Bayes Classifier

Training On a une distribution de données équivalente à celle d'une distribution de Bernouilli, donc, on va utiliser la variante BernouilliNB de Naive Bayes.

[ ]:
```
clf_nb = BernoulliNB()
clf_nb.fit(train_set, y_train)
```

[ ]:
```
BernoulliNB(alpha=1.0, binarize=0.0, class_prior=None, fit_prior=True)
```

Prédiction des données

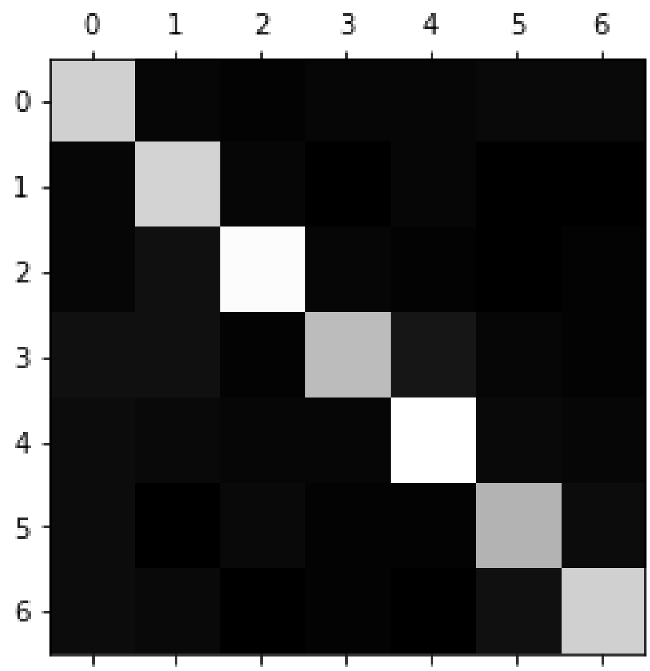
[ ]:
```
y_nb_predicted = clf_nb.predict(test_set)
```

Évaluation du modèle

[ ]:
```
#Matrice de confusion
conf_mx = confusion_matrix(y_test, y_nb_predicted)
print(conf_mx)
```

```
[[65  2  1  2  2  3  3]
 [ 2 66  2  0  2  0  0]
 [ 2  5 79  2  1  0  1]
 [ 5  5  1 59  7  2  1]
 [ 4  3  2  2 80  3  2]
 [ 4  0  3  1  1 56  4]
 [ 4  3  0  1  0  5 65]]
```

[ ]:
```
plt.matshow(conf_mx, cmap=plt.cm.gray)
plt.show()
```



[ ]:
```
#Accuracy avec cross validation
cross_val_score(clf_nb, X_resampled, y_resampled, cv=4, scoring="accuracy")
```

[ ]:
```
array([0.80992908, 0.79971591, 0.83806818, 0.85227273])
```

[ ]:
```
#Calcul de la precision et du rappel
print(precision_score(y_test, y_nb_predicted, average='macro'))
print(recall_score(y_test, y_nb_predicted, average='macro'))
f1_nb = f1_score(y_test, y_nb_predicted, average='macro')
print(f1_nb)
f1_scores["NB Classifier sur X"] = f1_nb
```

```
0.8352749916302903
0.8347912353347136
0.8330727434959905
```

[ ]:
```
normalized_mutual_info_score(y_test, y_nb_predicted)
```

[ ]:
```
0.6444266142644927
```

3.1.3 2. RF Classifier

Training

[ ]:
```
#Recherche des paramètres par grid search
def rf_grid_search(X, y):
    feature_mode = ['sqrt', 'log2']
    param_grid_search = {'max_features': feature_mode}

    grid_search = GridSearchCV(RandomForestClassifier(n_jobs=-1),␣
↪param_grid_search, scoring='f1_macro', return_train_score=True)
    grid_search.fit(X, y)

    return grid_search.best_params_
```

[ ]:
```
print(rf_grid_search(train_set, y_train))
```

```
{'max_features': 'log2'}
```

[ ]:
```
rnd_fr_clf = RandomForestClassifier(max_features = 'log2', n_jobs=-1)
rnd_fr_clf.fit(train_set, y_train)
```

[ ]:
```
RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                       criterion='gini', max_depth=None, max_features='log2',
                       max_leaf_nodes=None, max_samples=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, n_estimators=100,
                       n_jobs=-1, oob_score=False, random_state=None, verbose=0,
                       warm_start=False)
```

Prédiction des données

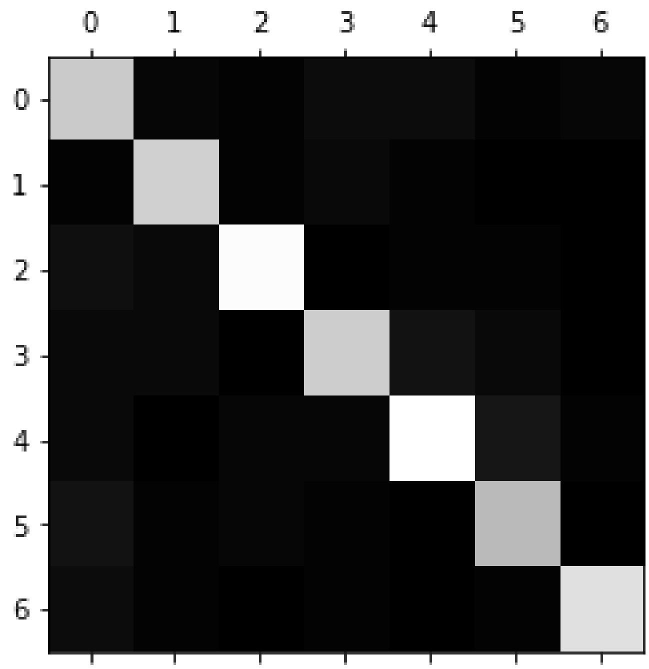
[ ]:
```
rnd_fr_predicted = rnd_fr_clf.predict(test_set)
```

Évaluation du modèle

[ ]:
```
#Matrice de confusion
conf_mx = confusion_matrix(y_test, rnd_fr_predicted)
print(conf_mx)
```

```
[[64  2  1  4  4  1  2]
 [ 1 66  1  3  1  0  0]
 [ 5  3 80  0  1  1  0]
 [ 3  3  0 65  6  3  0]
 [ 3  0  2  2 81  7  1]
 [ 6  1  2  1  0 59  0]
 [ 4  1  0  1  0  1 71]]
```

[ ]:
```
plt.matshow(conf_mx, cmap=plt.cm.gray)
plt.show()
```



[ ]:
```
#Cross validation
print(cross_val_score(rnd_fr_clf, X, L, cv=3, scoring="accuracy"))
```

```
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
```

```
[0.73089701 0.79291251 0.74279379]
```

```
[ ]: #Precision, rappel et f1 score
f1_rf = f1_score(y_test, rnd_fr_predicted, average='macro')

print(precision_score(y_test, rnd_fr_predicted, average='macro'))
print(recall_score(y_test, rnd_fr_predicted, average='macro'))
print(f1_score(y_test, rnd_fr_predicted,average='macro'))

f1_scores["Random Forest sur X"] = f1_rf
```

```
0.863996351573838
0.863949607156129
0.8632909650395633
```

```
[ ]: normalized_mutual_info_score(y_test, rnd_fr_predicted)
```

```
[ ]: 0.704742156563739
```

3.1.4 *Modèle de scoring*

Nous allons utilisation des différentes techniques de classification sur M supervisée vue en cours pour créer un modèle de scoring.

```
[ ]: X, W, L = cora_mat['fea'], cora_mat['W'], cora_mat['gnd']
```

```
[ ]: D = np.diag(np.sum(W, axis = 1))
```

```
[ ]: M = np.dot(np.dot(np.linalg.inv(D), W), X)
```

Under/Over sampling data

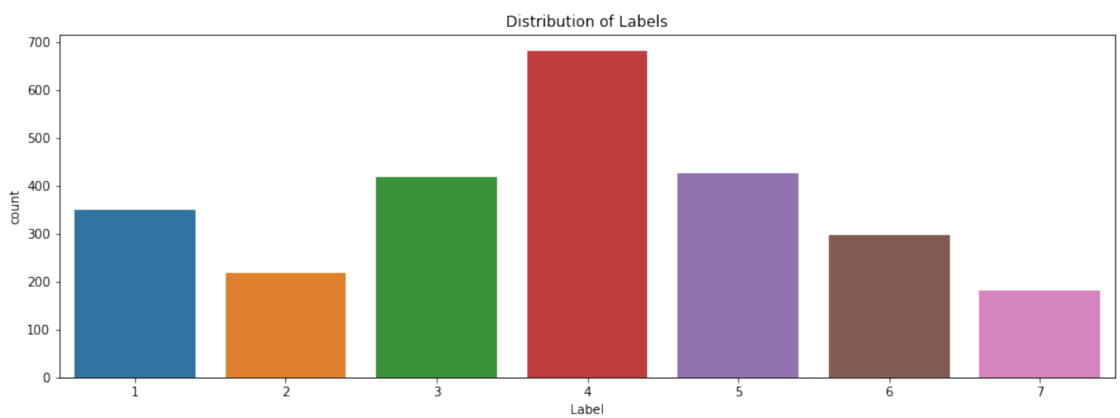
```
[ ]: #Undersampling de la classe 4
ncl = NeighbourhoodCleaningRule(return_indices=False, sampling_strategy={4 :␣
↪600})
X_resampled, y_resampled = ncl.fit_sample(M, L)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:760:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
ravel().
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
```

```
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
```

[ ]:
```
fig, ax = plt.subplots(figsize=(15,5))
ax = sns.countplot(x = y_resampled.flatten())
ax.set_title('Distribution of Labels')
ax.set_xlabel('Label')
```

[ ]:
```
Text(0.5, 0, 'Label')
```

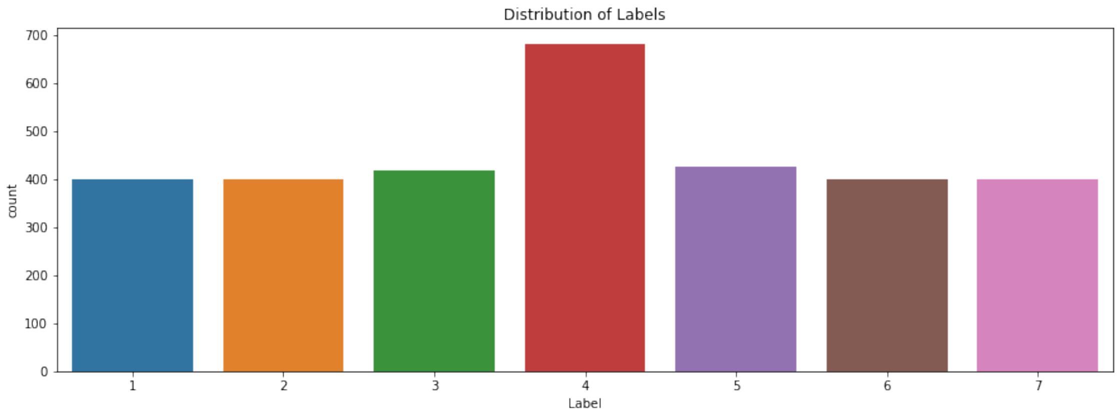


[ ]:
```
# Équilibrage des données en utilisant ROS over-sampling tant qu'on a pas bcp␣
↪de data
ros = RandomOverSampler(sampling_strategy={1 : 400, 2 : 400, 7 : 400, 6 : 400})
X_resampled, y_resampled = ros.fit_sample(X_resampled, y_resampled)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function safe_indexing is deprecated; safe_indexing is deprecated
in version 0.22 and will be removed in version 0.24.
  warnings.warn(msg, category=FutureWarning)
```

[ ]:
```
fig, ax = plt.subplots(figsize=(15,5))
ax = sns.countplot(x = y_resampled.flatten())
ax.set_title('Distribution of Labels')
ax.set_xlabel('Label')
```

[ ]: Text(0.5, 0, 'Label')

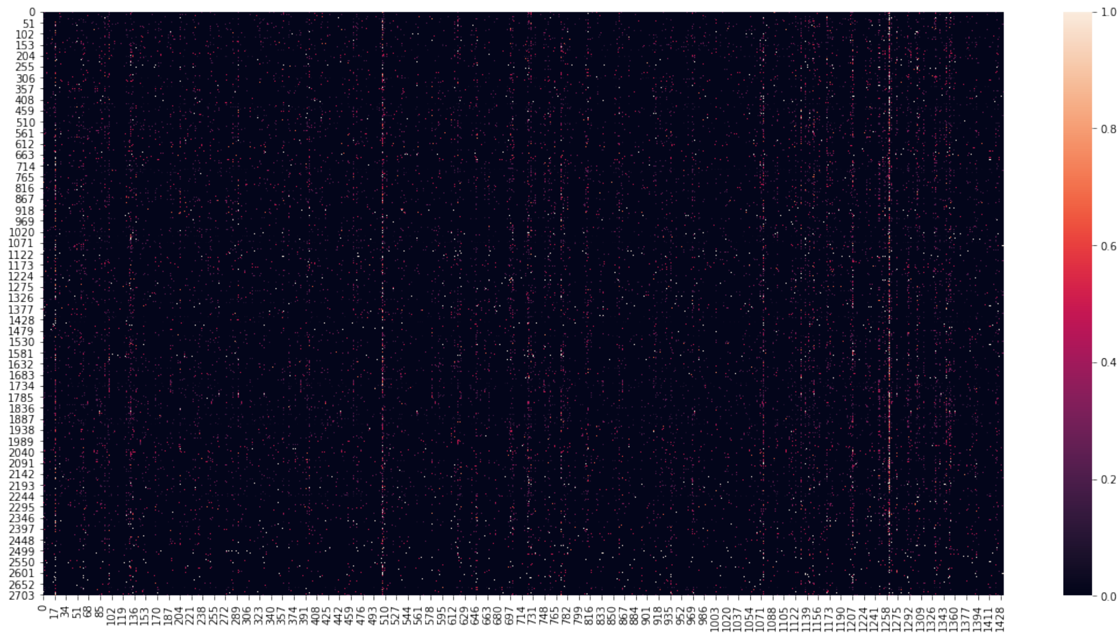


Séparation des données train/test sets

[ ]:
```
def split_train_test(data, y_label, test_ratio):
  shuffled_indices = np.random.permutation(len(data))
  test_set_size = int(len(data) * test_ratio)
  test_indices = shuffled_indices[:test_set_size]
  train_indices = shuffled_indices[test_set_size:]
  return data[train_indices], data[test_indices], y_label[train_indices],␣
 ↪y_label[test_indices]
```

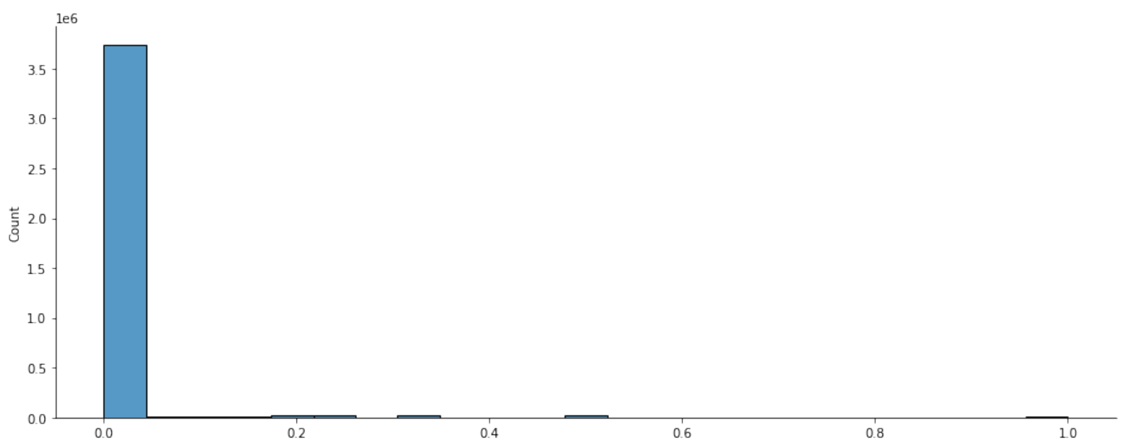
[ ]:
```
#Split data into train /test sets
train_set, test_set, y_train, y_test = split_train_test(M, L, 0.2)
```

[ ]:
```
# Visualiser le dataset dans sa totalité
fig, ax = plt.subplots(figsize=(20,10))
ax = sns.heatmap(M)
```



[ ]:
```
# Visualiser la distribution des données du dataset
sns.displot(M.flatten(), aspect=2.5)
```

[ ]: <seaborn.axisgrid.FacetGrid at 0x7f9687f2ea10>



1. Naive Bayes Classifier (Multinomial)

Training

[ ]:
```
clf_mnb = MultinomialNB()
clf_mnb.fit(train_set, y_train)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:760:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
ravel().
  y = column_or_1d(y, warn=True)
```

[ ]:
```
MultinomialNB(alpha=1.0, class_prior=None, fit_prior=True)
```

Prédiction des données

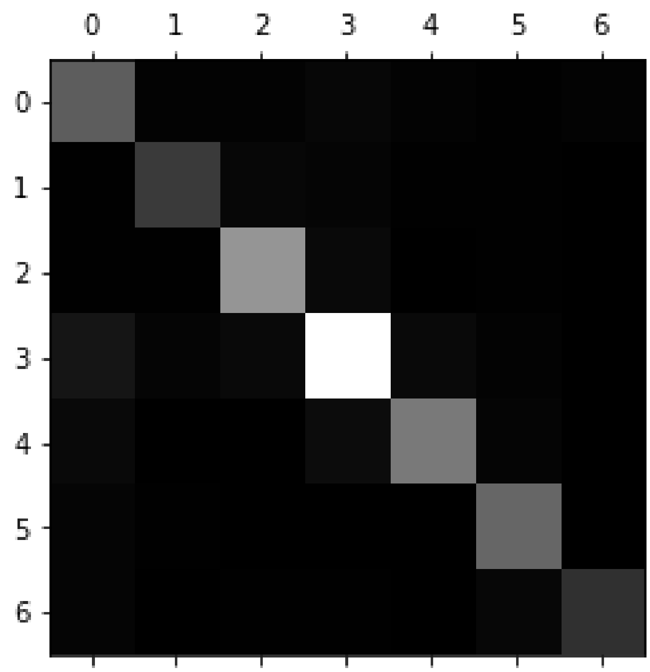
[ ]:
```
y_mnb_predicted = clf_mnb.predict(test_set)
```

Évaluation du modèle

[ ]:
```
#Matrice de confusion
conf_mx = confusion_matrix(y_test, y_mnb_predicted)
print(conf_mx)
```

```
[[ 51   2   2   4   2   1   2]
 [  1  32   4   3   1   1   0]
 [  1   1  82   5   0   1   0]
 [ 12   3   5 140   5   2   0]
 [  5   0   0   7  67   3   0]
 [  3   1   0   0   0  56   0]
 [  3   0   1   1   0   4  27]]
```

[ ]:
```
plt.matshow(conf_mx, cmap=plt.cm.gray)
plt.show()
```




```
[ ]: #Accuracy avec cross validation
     cross_val_score(clf_mnb, M, L, cv=4, scoring="accuracy")
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:760:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
ravel().
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:760:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
ravel().
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:760:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
ravel().
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/validation.py:760:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
ravel().
  y = column_or_1d(y, warn=True)
```

```
[ ]: array([0.83456425, 0.83456425, 0.85081241, 0.81093058])
```

[ ]:
```
#Calcul de la precision et du rappel
print(precision_score(y_test, y_mnb_predicted, average='macro'))
print(recall_score(y_test, y_mnb_predicted, average='macro'))
f1_mnb = f1_score(y_test, y_mnb_predicted, average='macro')
print(f1_mnb)
f1_scores["NB Classifier sur M"] = f1_mnb
```

```
0.8409718722114776
0.8298029614820467
0.8322201088314418
```

[ ]:
```
normalized_mutual_info_score(y_test.reshape((y_test.shape[0])), y_mnb_predicted)
```

[ ]:
```
0.6522031088587515
```

2. KNN Classifier En calculant M, on a prit en compte la notion de profil, il est donc possible d'utiliser un algorithme qui se base sur la distance euclidienne pour calculer la proximité entre les différents individus

Training

[ ]:
```
clf_knn = KNeighborsClassifier(n_neighbors=10, metric='euclidean')
clf_knn.fit(train_set, y_train)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples, ), for example using
ravel().
```

[ ]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='euclidean',
                     metric_params=None, n_jobs=None, n_neighbors=10, p=2,
                     weights='uniform')
```

Prédiction des données

[ ]:
```
y_knn_pred = clf_knn.predict(test_set)
```

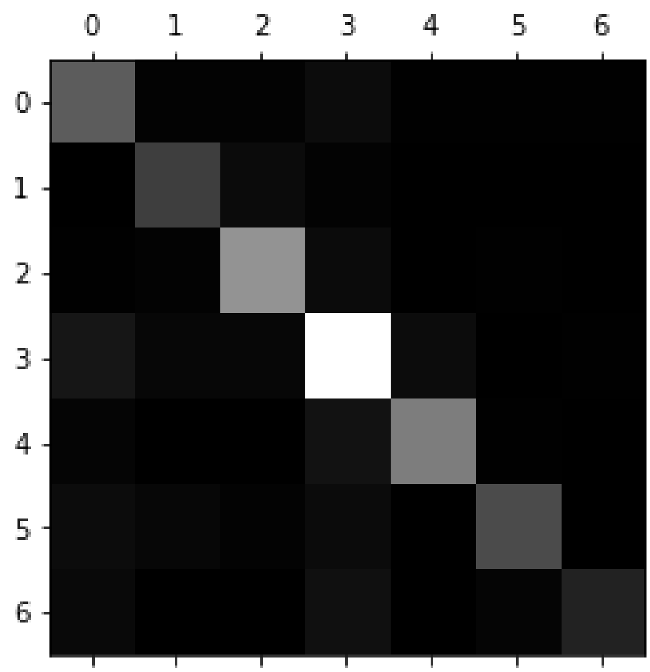
Évaluation du modèle

[ ]:
```
#Matrice de confusion
conf_mx = confusion_matrix(y_test, y_knn_pred)
print(conf_mx)
```

```
[[ 50   2   2   7   1   1   1]
 [  0  34   6   2   0   0   0]
 [  1   2  80   6   0   1   0]
```

```
 [ 12   4   4 139   7   0   1]
 [  3   0   0  10  68   1   0]
 [  7   4   2   6   0  41   0]
 [  5   0   0   9   0   3  19]]
```

[ ]:
```python
plt.matshow(conf_mx, cmap=plt.cm.gray)
plt.show()
```



[ ]:
```python
#Accuracy avec cross validation
cross_val_score(clf_knn, M, L, cv=4, scoring="accuracy")
```

```
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples, ), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples, ), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples, ), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
```

```
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples, ), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
```

[ ]:
```
array([0.80354505, 0.79911374, 0.79172821, 0.80649926])
```

[ ]:
```
#Calcul de la precision et du rappel
print(precision_score(y_test, y_knn_pred, average='macro'))
print(recall_score(y_test, y_knn_pred, average='macro'))
f1_mnb = f1_score(y_test, y_knn_pred, average='macro')
print(f1_mnb)
f1_scores["KNN sur M"] = f1_mnb
```

```
0.8113707701205328
0.7646253473640077
0.7776810501211725
```

[ ]:
```
normalized_mutual_info_score(y_test.reshape((541)), y_knn_pred)
```

[ ]:
```
0.5874657335267601
```

3. RF Classifier

Training

[ ]:
```
#Recherche des paramètres par grid search
def rf_grid_search(X, y):
    feature_mode = ['sqrt', 'log2']
    param_grid_search = {'max_features': feature_mode}

    grid_search = GridSearchCV(RandomForestClassifier(n_jobs=-1),␣
 ↪param_grid_search, scoring='f1_macro', return_train_score=True)
    grid_search.fit(X, y)

    return grid_search.best_params_
```

[ ]:
```
print(rf_grid_search(train_set, y_train))
```

```
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
```

```
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-packages/sklearn/model_selection/_search.py:739:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples,), for example using
ravel().
  self.best_estimator_.fit(X, y, **fit_params)
```

```
{'max_features': 'sqrt'}
```

```
[ ]: rnd_fr_clf = RandomForestClassifier(max_features = 'sqrt', n_jobs=-1)
     rnd_fr_clf.fit(train_set, y_train)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:2:
DataConversionWarning: A column-vector y was passed when a 1d array was
expected. Please change the shape of y to (n_samples,), for example using
ravel().
```

```
[ ]: RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight=None,
                            criterion='gini', max_depth=None, max_features='sqrt',
                            max_leaf_nodes=None, max_samples=None,
                            min_impurity_decrease=0.0, min_impurity_split=None,
                            min_samples_leaf=1, min_samples_split=2,
                            min_weight_fraction_leaf=0.0, n_estimators=100,
                            n_jobs=-1, oob_score=False, random_state=None, verbose=0,
                            warm_start=False)
```

Prédiction des données

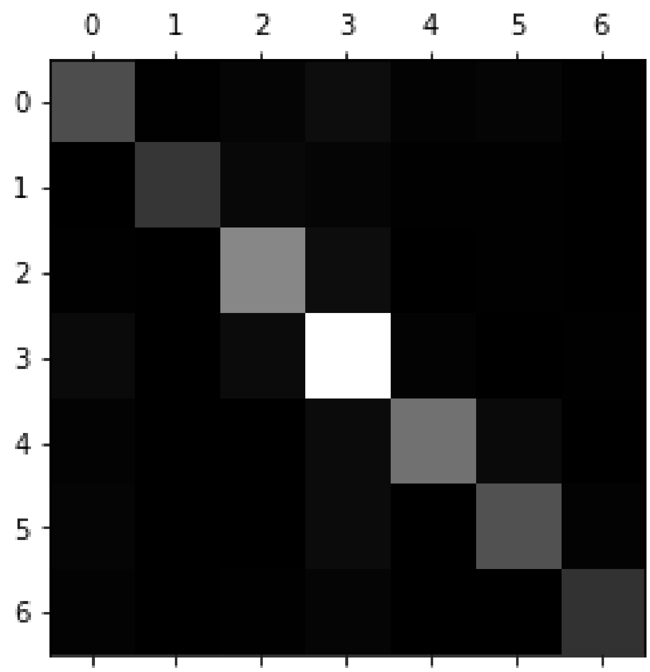
```
[ ]: rnd_fr_predicted = rnd_fr_clf.predict(test_set)
```

Évaluation du modèle

```
[ ]: #Matrice de confusion
     conf_mx = confusion_matrix(y_test, rnd_fr_predicted)
     print(conf_mx)
```

```
[[ 46   1   3   8   2   3   1]
 [  0  32   5   3   1   1   0]
 [  1   0  80   8   0   1   0]
 [  6   0   7 151   2   0   1]
 [  2   0   0   7  67   6   0]
 [  3   0   0   7   0  48   2]
 [  2   0   1   3   0   0  30]]
```

```
[ ]: plt.matshow(conf_mx, cmap=plt.cm.gray)
     plt.show()
```



[ ]:
```
#Cross validation
print(cross_val_score(rnd_fr_clf, M, L, cv=3, scoring="accuracy"))
```

```
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
/usr/local/lib/python3.7/dist-
packages/sklearn/model_selection/_validation.py:515: DataConversionWarning: A
column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples,), for example using ravel().
  estimator.fit(X_train, y_train, **fit_params)
```

```
[0.80730897 0.84717608 0.82372506]
```

[ ]:
```
#Precision, rappel et f1 score
f1_rf = f1_score(y_test, rnd_fr_predicted, average='macro')

print(precision_score(y_test, rnd_fr_predicted, average='macro'))
print(recall_score(y_test, rnd_fr_predicted, average='macro'))
```

```
print(f1_score(y_test, rnd_fr_predicted,average='macro'))

f1_scores["Random Forest sur M"] = f1_rf
```

```
0.8576644884969912
0.817734538803594
0.8346552331355523
```

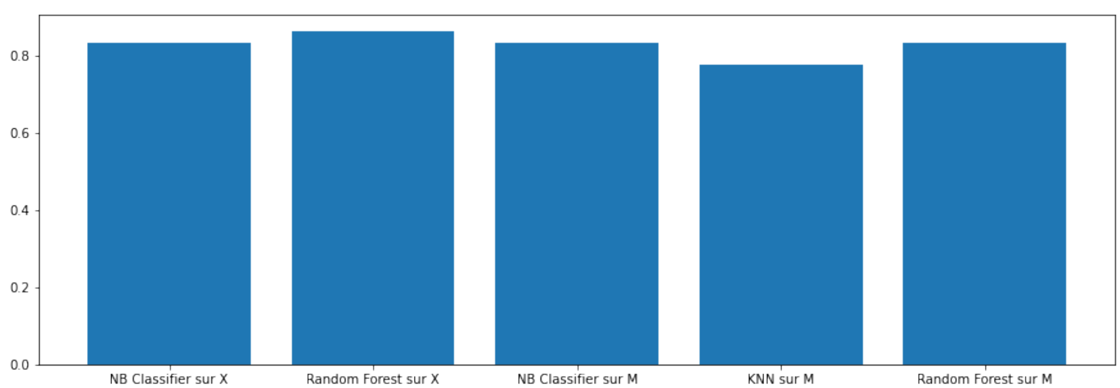
[ ]:
```
normalized_mutual_info_score(y_test.reshape((y_test.shape[0])),␣
↪rnd_fr_predicted)
```

[ ]:
```
0.649844877317438
```

3.1.5 Comparaison des différents modèles

[ ]:
```
# Afficher les Scores F1 pour chaque méthode
plt.figure(figsize=(15,5))
plt.bar(range(len(f1_scores)), list(f1_scores.values()), align='center')
plt.xticks(range(len(f1_scores)), list(f1_scores.keys()))
```

[ ]:
```
([<matplotlib.axis.XTick at 0x7f96908e5890>,
  <matplotlib.axis.XTick at 0x7f96908e5c90>,
  <matplotlib.axis.XTick at 0x7f96909ce910>,
  <matplotlib.axis.XTick at 0x7f96842a6210>,
  <matplotlib.axis.XTick at 0x7f96842a6750>],
 [Text(0, 0, 'NB Classifier sur X'),
  Text(0, 0, 'Random Forest sur X'),
  Text(0, 0, 'NB Classifier sur M'),
  Text(0, 0, 'KNN sur M'),
  Text(0, 0, 'Random Forest sur M')])
```



Le meilleur modèle est donc :

En utilisant X ==> **Random Forest**

En utilisant M ==> **Naive Bayes**

4 *CiteSeer data*

4.1 Importations

[ ]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler
from scipy.io import loadmat
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.datasets import make_moons, make_circles, make_classification
from sklearn.neural_network import MLPClassifier
from sklearn.neighbors import KNeighborsClassifier
from imblearn.over_sampling  import RandomOverSampler
from sklearn.svm import SVC
from sklearn.gaussian_process import GaussianProcessClassifier
from sklearn.gaussian_process.kernels import RBF
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,␣
↪GradientBoostingClassifier, ExtraTreesClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.discriminant_analysis import QuadraticDiscriminantAnalysis,␣
↪LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import precision_recall_curve, roc_curve,␣
↪plot_precision_recall_curve, average_precision_score, auc
import matplotlib.pyplot as plt
from tensorflow.keras.utils import to_categorical
```

Dans cette partie nous allons faire une analyse exploratoire des données CiteSeer puis nous allons faire le traitement de ces données. Ensuite nous allons comparer plusieurs algorithmes appliqués sur ces données.

4.2 Analyse exploratoire des données

4.2.1 *Lecture des données*

[ ]:
```
citeseer_mat = loadmat('/content/citeseer.mat')
citeseer_mat
```

[ ]:
```
{'W': array([[0, 0, 0, …, 0, 0, 0],
        [0, 0, 0, …, 0, 0, 0],
        [0, 0, 0, …, 0, 0, 0],
        …,
        [0, 0, 0, …, 0, 0, 0],
        [0, 0, 0, …, 0, 0, 0],
        [0, 0, 0, …, 0, 0, 0]], dtype=uint8),
 '__globals__': [],
 '__header__': b'MATLAB 5.0 MAT-file, Platform: PCWIN64, Created on: Fri Jan 18
15:27:08 2019',
 '__version__': '1.0',
 'fea': array([[0, 0, 0, …, 0, 0, 0],
        [0, 0, 0, …, 0, 0, 0],
        [0, 0, 0, …, 0, 0, 0],
        …,
        [0, 0, 0, …, 0, 0, 0],
        [0, 0, 0, …, 0, 0, 0],
        [0, 0, 0, …, 0, 0, 0]], dtype=uint8),
 'gnd': array([[4],
        [2],
        [6],
        …,
        [4],
        [2],
        [6]], dtype=uint8)}
```

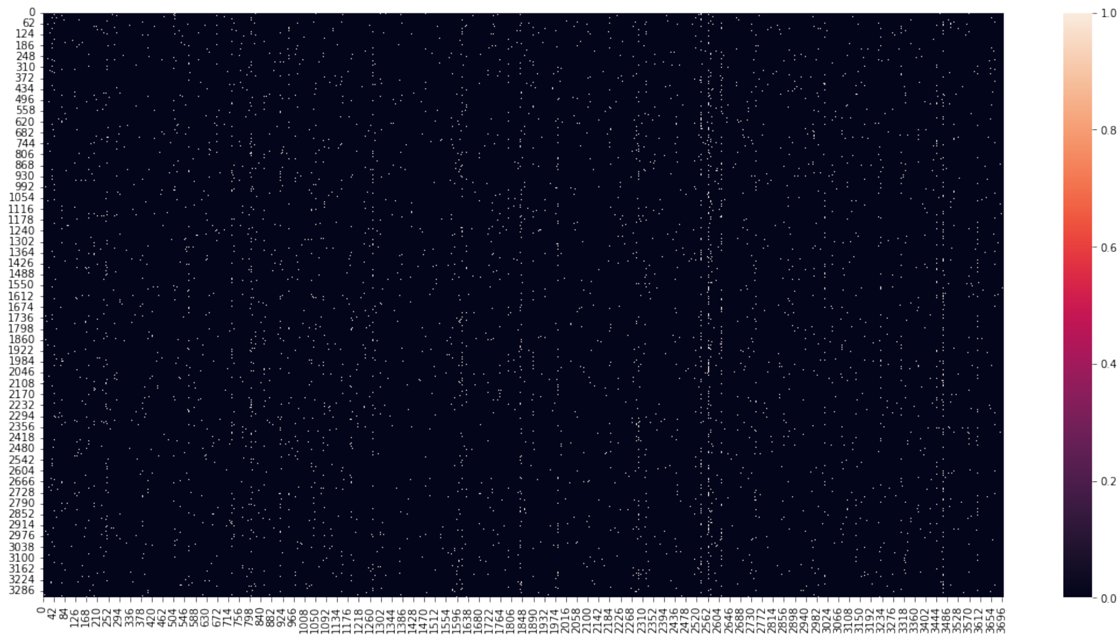
[ ]:
```
X, W, L = citeseer_mat['fea'], citeseer_mat['W'], citeseer_mat['gnd']
```

[ ]:
```
np.isnan(X).any()
```

[ ]:
```
False
```

4.2.2 Visualisation des données

[ ]:
```
fig, ax = plt.subplots(figsize=(20,10))
ax = sns.heatmap(X)
```

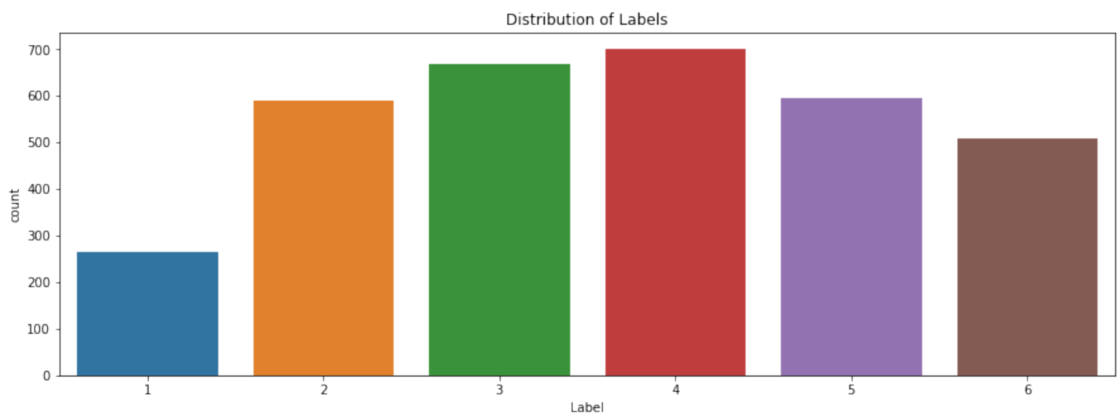


```
[ ]: #Les valeurs des données => Données binaires
     set(W.flatten())
```

```
[ ]: {0, 1}
```

```
[ ]: #Distribution des labels
     #Distribution déséquilibrée
     fig, ax = plt.subplots(figsize=(15,5))
     ax = sns.countplot(x = L.flatten())
     ax.set_title('Distribution of Labels')
     ax.set_xlabel('Label')
```

```
[ ]: Text(0.5, 0, 'Label')
```



Suite à la visualisation des données, on remarque que les classes sont déséquilibrées.La classe 1 est minoritaire. \ Nous allons donc essayer d'équilibrer ces classes.

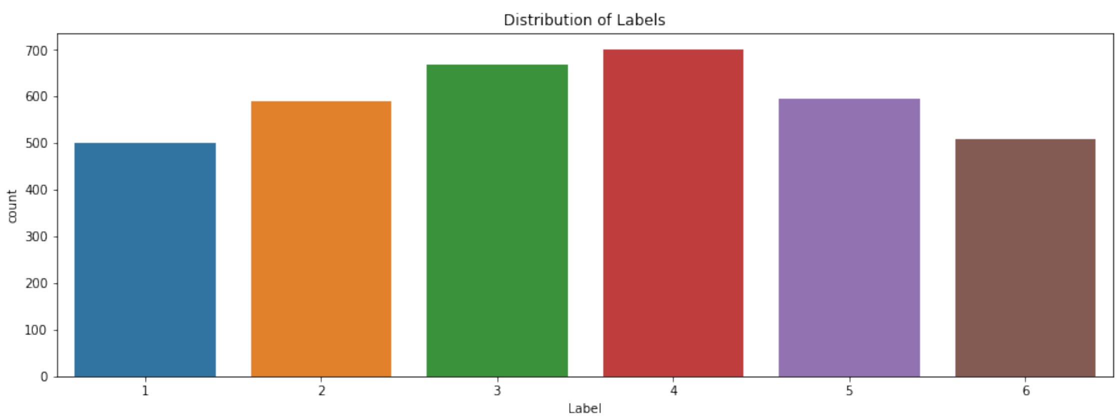
4.2.3 *Over sampling data*

Équilibrage des données en utilisant ROS over—sampling tant qu'on a pas beaucoup de data.

[ ]:
```
ros = RandomOverSampler(sampling_strategy={1 : 500})
X_resampled, y_resampled = ros.fit_resample(X, L)
```

[ ]:
```
fig, ax = plt.subplots(figsize=(15,5))
ax = sns.countplot(x = y_resampled.flatten())
ax.set_title('Distribution of Labels')
ax.set_xlabel('Label')
```

[ ]: Text(0.5, 0, 'Label')



Nous remarquons qu'après l'application de la méthode ROS over—sampling, nous avons pu équilibrer la data.

4.3 *Classification*

Cette fonction permet d'évaluer différent algorithmes appliqués sur son input (data X, Y).

[ ]:
```
def evaluate_aglo(X, y, nbr_classes):

  names = ["Nearest Neighbors", "Linear SVM", "RBF SVM", "Gaussian Process",
         "Decision Tree", "Random Forest", "Neural Net", "AdaBoost",
```

```
        "Naive Bayes", "QDA", "Gradient Boosting", "Logistic Regression",␣
↪"Extra Trees", "LDA"]
 h = .02
 classifiers = [
     KNeighborsClassifier(3),
     SVC(kernel="linear", C=0.025),
     SVC(gamma=2, C=1),
     GaussianProcessClassifier(1.0 * RBF(1.0)),
     DecisionTreeClassifier(max_depth=5),
     RandomForestClassifier(max_depth=5, n_estimators=10, max_features=1),
     MLPClassifier(alpha=1, max_iter=1000),
     AdaBoostClassifier(),
     GaussianNB(),
     QuadraticDiscriminantAnalysis(),
     GradientBoostingClassifier(),
     LogisticRegression(),
     ExtraTreesClassifier(),
     LinearDiscriminantAnalysis()]

 # preprocess dataset, split into training and test part
 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=.3,␣
↪random_state=42)

 precision_clf = dict()
 recall_clf = dict()
 average_precision_clf = dict()
 auc_clf = dict()
 acc_clf = dict()

 # iterate over classifiers
 for name, clf in zip(names, classifiers):

     print('<-- {0:^50} -->'.format(name))

     clf.fit(X_train, y_train)
     score = clf.score(X_test, y_test)
     print("Accuracy achieved by {} ".format(name, 'G') + str(score))
     acc_clf[name] = score

     fpr, tpr, thresholds = roc_curve(y_test, clf.predict(X_test), pos_label=2)
     print("Area Under the Curve achieved by {} ".format(name, 'G') +␣
↪str(auc(fpr, tpr)))
     auc_c = dict()
     auc_c['auc'] = auc(fpr, tpr)
     auc_c['fpr'] = fpr
     auc_c['tpr'] = tpr
     auc_clf[name] = auc_c
```

```
        # For each class
        precision = dict()
        recall = dict()
        average_precision = dict()
        for i in range(1, nbr_classes):
            precision[i], recall[i], _ =␣
↪precision_recall_curve(to_categorical(y_test, num_classes=nbr_classes)[:, i]␣
↪, to_categorical(clf.predict(X_test), num_classes=nbr_classes)[:, i])
            average_precision[i] = average_precision_score(to_categorical(y_test,␣
↪num_classes=nbr_classes)[:, i] , to_categorical(clf.predict(X_test),␣
↪num_classes=nbr_classes)[:, i])

        # A "micro-average": quantifying score on all classes jointly
        precision["micro"], recall["micro"], _ =␣
↪precision_recall_curve(to_categorical(y_test, num_classes=nbr_classes)[:,1:].
↪ravel() , to_categorical(clf.predict(X_test), num_classes=nbr_classes)[:,1:].
↪ravel())
        average_precision["micro"] =␣
↪average_precision_score(to_categorical(y_test, num_classes=nbr_classes)[:,␣
↪i] , to_categorical(clf.predict(X_test), num_classes=nbr_classes)[:, i],
                                                         average="micro")
        print('Average precision score, micro-averaged over all classes: {0:0.
↪2f}'.format(average_precision["micro"]))
        print("\n\n")

        precision_clf[name] = precision
        recall_clf[name] = recall
        average_precision_clf[name] = average_precision

    return precision_clf, auc_clf, recall_clf, names
```

4.3.1 *Matrice X*

```
[ ]: precision_clf, auc_clf, recall_clf, names = evaluate_aglo(X_resampled,␣
      ↪y_resampled, 7)
```

```
<--                 Nearest Neighbors                  -->
Accuracy achieved by Nearest Neighbors 0.1618334892422825
Area Under the Curve achieved by Nearest Neighbors 0.5046486274191146
Average precision score, micro-averaged over all classes: 0.16



<--                     Linear SVM                     -->
Accuracy achieved by Linear SVM 0.7380729653882133
```

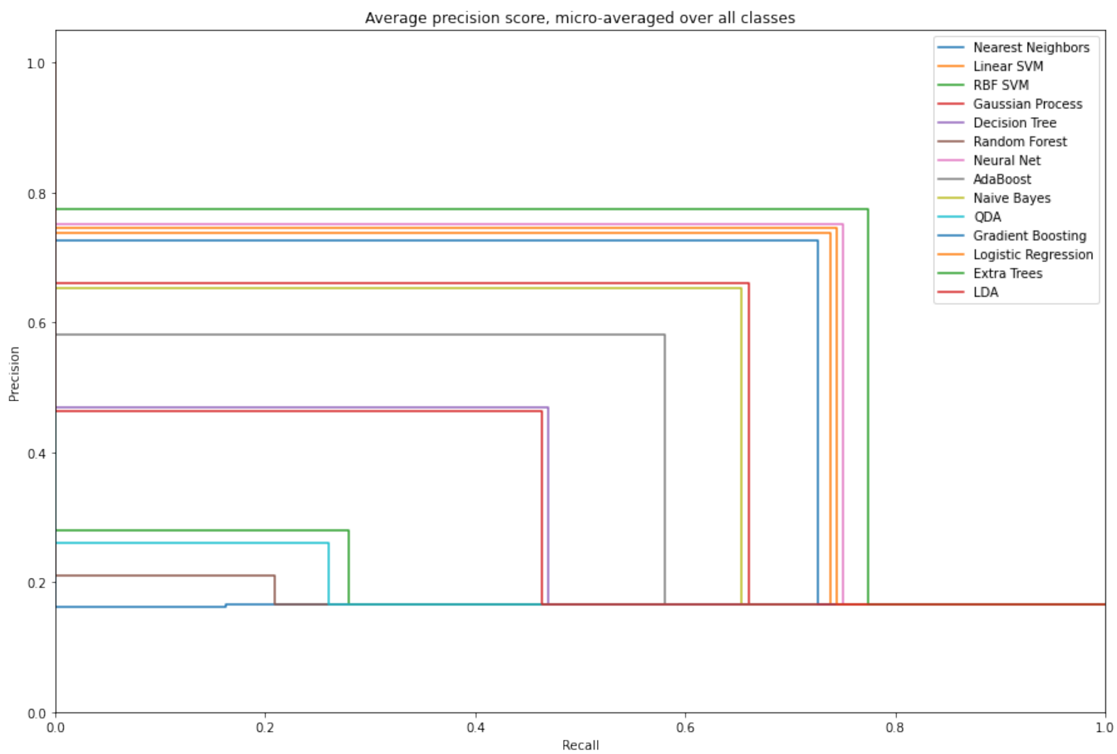
```
Area Under the Curve achieved by Linear SVM 0.24197578515418683
Average precision score, micro-averaged over all classes: 0.62



<--                     RBF SVM                        -->
Accuracy achieved by RBF SVM 0.27970065481758655
Area Under the Curve achieved by RBF SVM 0.5535320088300221
Average precision score, micro-averaged over all classes: 0.15



<--                 Gaussian Process                   -->
Accuracy achieved by Gaussian Process 0.6604303086997194
Area Under the Curve achieved by Gaussian Process 0.3347553460908192
Average precision score, micro-averaged over all classes: 0.60



<--                  Decision Tree                     -->
Accuracy achieved by Decision Tree 0.4695977549111319
Area Under the Curve achieved by Decision Tree 0.36541664973794336
Average precision score, micro-averaged over all classes: 0.30



<--                  Random Forest                     -->
Accuracy achieved by Random Forest 0.20954162768942938
Area Under the Curve achieved by Random Forest 0.48907420197998347
Average precision score, micro-averaged over all classes: 0.15



<--                    Neural Net                      -->
Accuracy achieved by Neural Net 0.7502338634237605
Area Under the Curve achieved by Neural Net 0.25619252698438494
Average precision score, micro-averaged over all classes: 0.61



<--                     AdaBoost                       -->
Accuracy achieved by AdaBoost 0.5809167446211413
Area Under the Curve achieved by AdaBoost 0.2655574967158276
Average precision score, micro-averaged over all classes: 0.46



<--                   Naive Bayes                      -->
```

```
Accuracy achieved by Naive Bayes 0.6529466791393826
Area Under the Curve achieved by Naive Bayes 0.30956202007069433
Average precision score, micro-averaged over all classes: 0.46



<--                        QDA                        -->
/usr/local/lib/python3.7/dist-packages/sklearn/discriminant_analysis.py:878:
UserWarning: Variables are collinear
  warnings.warn("Variables are collinear")
Accuracy achieved by QDA 0.2600561272217025
Area Under the Curve achieved by QDA 0.5769986050731998
Average precision score, micro-averaged over all classes: 0.15



<--                 Gradient Boosting                 -->
Accuracy achieved by Gradient Boosting 0.725912067352666
Area Under the Curve achieved by Gradient Boosting 0.25145587020409266
Average precision score, micro-averaged over all classes: 0.59



<--                Logistic Regression                -->
Accuracy achieved by Logistic Regression 0.744621141253508
Area Under the Curve achieved by Logistic Regression 0.26489389076233427
Average precision score, micro-averaged over all classes: 0.61



<--                    Extra Trees                    -->
Accuracy achieved by Extra Trees 0.774555659494855
Area Under the Curve achieved by Extra Trees 0.25394777827435366
Average precision score, micro-averaged over all classes: 0.64



<--                        LDA                        -->
Accuracy achieved by LDA 0.4630495790458372
Area Under the Curve achieved by LDA 0.4428587873616924
Average precision score, micro-averaged over all classes: 0.30
```

On remarque que le modèle avec l'accuracy la plus elevée est Extra Trees avec un précision de 0.78 un avergage precision score 0.64 et un AUC de 0.26

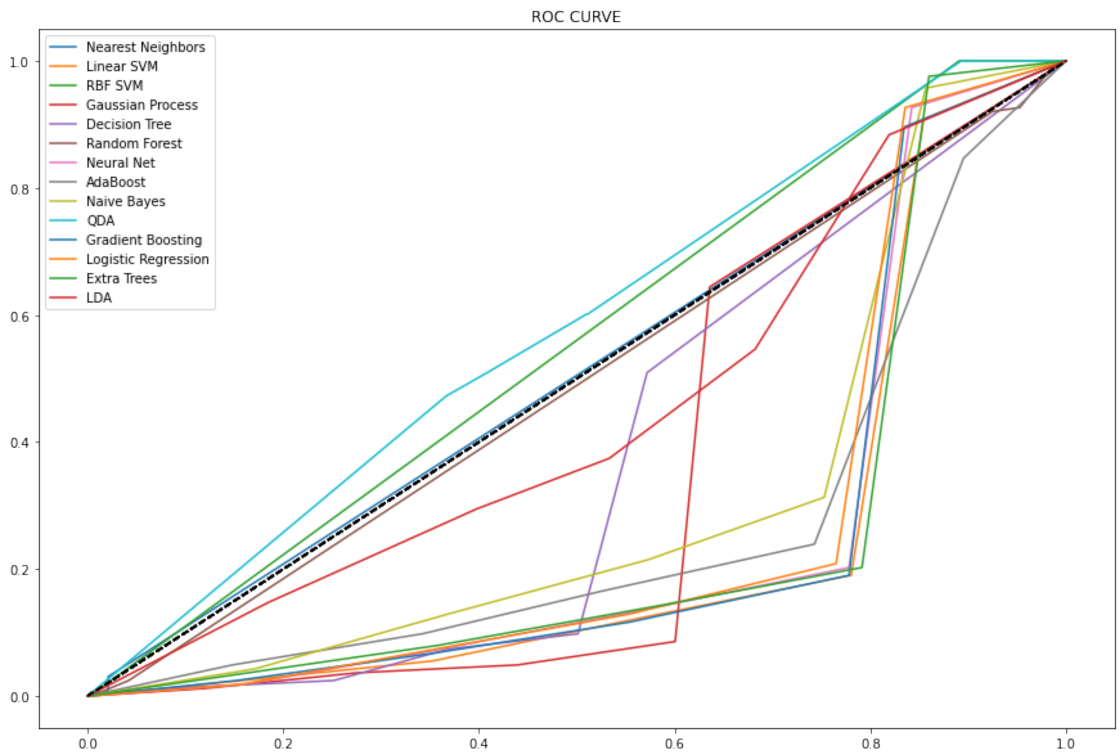
[ ]:
```python
plt.figure(figsize=(15,10))
for model in names:
    plt.step(recall_clf[model]['micro'], precision_clf[model]['micro'],␣
 ↪where='post', label=model)
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.ylim([0.0, 1.05])
    plt.xlim([0.0, 1.0])
plt.legend()
plt.title('Average precision score, micro-averaged over all classes')
```

[ ]: Text(0.5, 1.0, 'Average precision score, micro-averaged over all classes')



[ ]:
```python
plt.figure(figsize=(15,10))
for model in names:
  plt.plot(auc_clf[model]['fpr'], auc_clf[model]['tpr'], label=model)
  plt.plot([0,1], [0,1], 'k--')
plt.legend()
plt.title('ROC CURVE')
```

[ ]: Text(0.5, 1.0, 'ROC CURVE')



4.3.2 *Matrice M*

[ ]:
```
degrees = citeseer_mat['W'].sum(axis=0)
D = np.zeros((len(degrees), len(degrees)))
for i in range(len(degrees)):
  D[i, i] = 1/degrees[i]
```

[ ]:
```
tmp = np.dot(citeseer_mat['W'], X)
M = np.dot(D, tmp)
```

[ ]:
```
precision_clf, auc_clf, recall_clf, names = evaluate_aglo(X_resampled,␣
 ↪y_resampled, 7)
```

```
<--                    Nearest Neighbors                  -->
Accuracy achieved by Nearest Neighbors 0.1618334892422825
Area Under the Curve achieved by Nearest Neighbors 0.5046486274191146
Average precision score, micro-averaged over all classes: 0.16



<--                        Linear SVM                     -->
Accuracy achieved by Linear SVM 0.7315247895229187
```

```
Area Under the Curve achieved by Linear SVM 0.2459912783217541
Average precision score, micro-averaged over all classes: 0.61



<--                      RBF SVM                        -->
Accuracy achieved by RBF SVM 0.2862488306828812
Area Under the Curve achieved by RBF SVM 0.5573951434878588
Average precision score, micro-averaged over all classes: 0.15



<--                  Gaussian Process                   -->
Accuracy achieved by Gaussian Process 0.64733395696913
Area Under the Curve achieved by Gaussian Process 0.33025230569211383
Average precision score, micro-averaged over all classes: 0.59



<--                   Decision Tree                     -->
Accuracy achieved by Decision Tree 0.4630495790458372
Area Under the Curve achieved by Decision Tree 0.38619157897587997
Average precision score, micro-averaged over all classes: 0.25



<--                   Random Forest                     -->
Accuracy achieved by Random Forest 0.323666978484565
Area Under the Curve achieved by Random Forest 0.41328769349530736
Average precision score, micro-averaged over all classes: 0.16



<--                     Neural Net                      -->
Accuracy achieved by Neural Net 0.7474275023386342
Area Under the Curve achieved by Neural Net 0.2651444358672246
Average precision score, micro-averaged over all classes: 0.61



<--                      AdaBoost                       -->
Accuracy achieved by AdaBoost 0.5902712815715622
Area Under the Curve achieved by AdaBoost 0.2710559460447731
Average precision score, micro-averaged over all classes: 0.44



<--                    Naive Bayes                      -->
```

```
Accuracy achieved by Naive Bayes 0.6538821328344246
Area Under the Curve achieved by Naive Bayes 0.31420387600048755
Average precision score, micro-averaged over all classes: 0.47



<--                       QDA                        -->
```

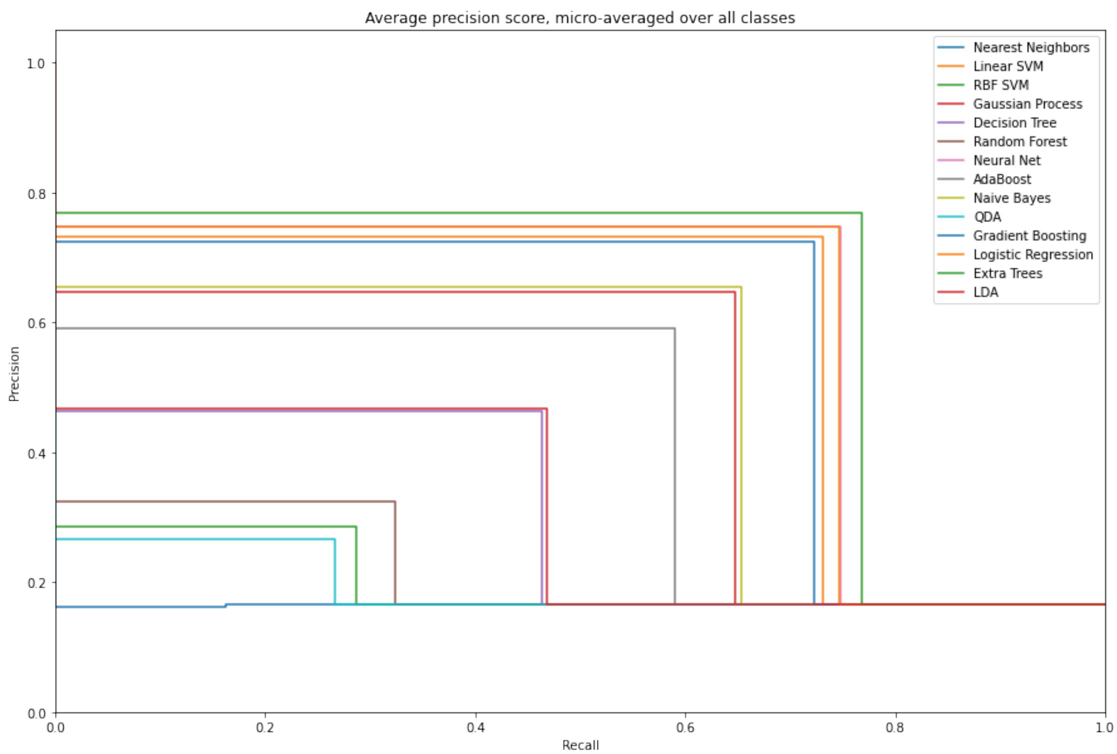
```
/usr/local/lib/python3.7/dist-packages/sklearn/discriminant_analysis.py:878:
UserWarning: Variables are collinear
  warnings.warn("Variables are collinear")
```

```
Accuracy achieved by QDA 0.2666043030869972
Area Under the Curve achieved by QDA 0.5759050095478
Average precision score, micro-averaged over all classes: 0.15



<--                Gradient Boosting                 -->
Accuracy achieved by Gradient Boosting 0.7231057062675398
Area Under the Curve achieved by Gradient Boosting 0.23377212584135754
Average precision score, micro-averaged over all classes: 0.59



<--               Logistic Regression                -->
Accuracy achieved by Logistic Regression 0.7464920486435921
Area Under the Curve achieved by Logistic Regression 0.2627405571581414
Average precision score, micro-averaged over all classes: 0.61



<--                   Extra Trees                    -->
Accuracy achieved by Extra Trees 0.7680074836295603
Area Under the Curve achieved by Extra Trees 0.2549228727366297
Average precision score, micro-averaged over all classes: 0.65



<--                       LDA                        -->
Accuracy achieved by LDA 0.4677268475210477
Area Under the Curve achieved by LDA 0.4479814190333022
Average precision score, micro-averaged over all classes: 0.30
```

On remarque que le modèle avec l'accuracy la plus elevée est Extra Trees avec un précision de 0.77 un avergage precision score 0.65 et un AUC de 0.25

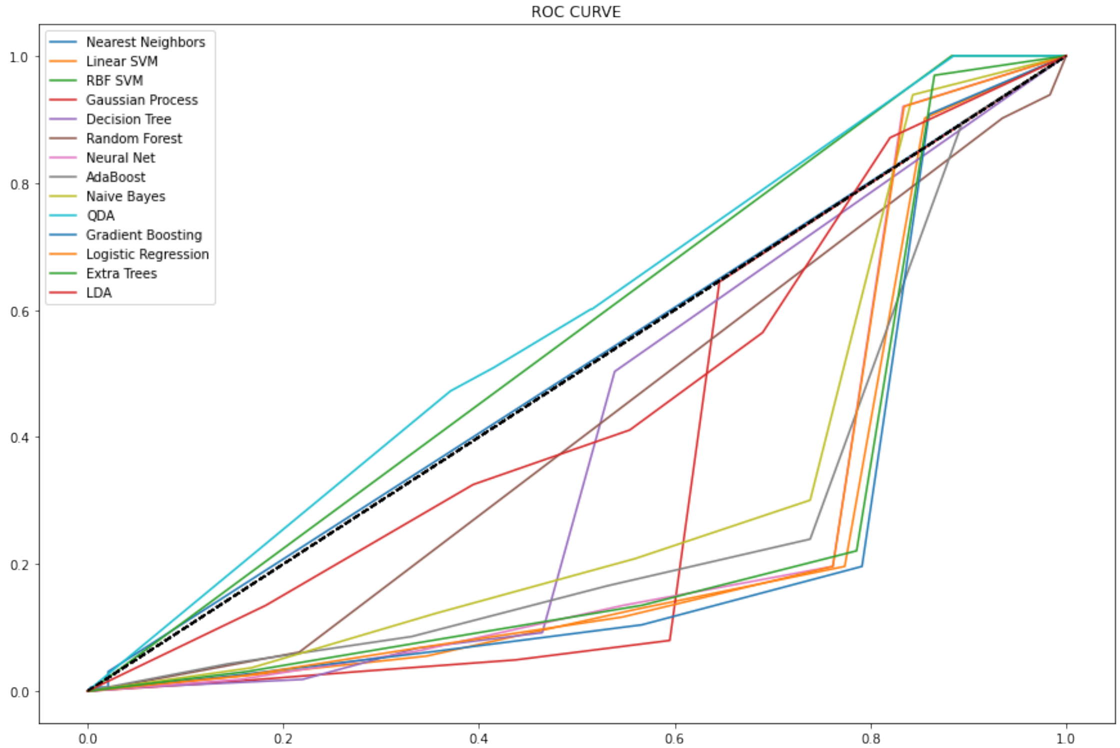
[ ]:
```
plt.figure(figsize=(15,10))
for model in names:
    plt.step(recall_clf[model]['micro'], precision_clf[model]['micro'],␣
↪where='post', label=model)
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.ylim([0.0, 1.05])
    plt.xlim([0.0, 1.0])
plt.legend()
plt.title('Average precision score, micro-averaged over all classes')
```

[ ]: Text(0.5, 1.0, 'Average precision score, micro-averaged over all classes')



[ ]:
```
plt.figure(figsize=(15,10))
for model in names:
  plt.plot(auc_clf[model]['fpr'], auc_clf[model]['tpr'], label=model)
  plt.plot([0,1], [0,1], 'k--')
plt.legend()
plt.title('ROC CURVE')
```

[ ]: Text(0.5, 1.0, 'ROC CURVE')



4.3.3 *Matrice W +I*

[ ]:
```
degrees = citeseer_mat['W'].sum(axis=0)
D = np.zeros((len(degrees), len(degrees)))
for i in range(len(degrees)):
  D[i, i] = 1/degrees[i]
```

[ ]:
```
tmp = np.dot(citeseer_mat['W']+np.diag(np.ones(len(degrees))), X)
M = np.dot(D, tmp)
```

[ ]:
```
precision_clf, auc_clf, recall_clf, names = evaluate_aglo(X_resampled,␣
 ↪y_resampled, 7)
```

```
<--                   Nearest Neighbors                   -->
Accuracy achieved by Nearest Neighbors 0.1618334892422825
Area Under the Curve achieved by Nearest Neighbors 0.5046486274191146
Average precision score, micro-averaged over all classes: 0.16



<--                       Linear SVM                      -->
Accuracy achieved by Linear SVM 0.7436856875584659
```

```
Area Under the Curve achieved by Linear SVM 0.2510800525467572
Average precision score, micro-averaged over all classes: 0.62



<--                      RBF SVM                      -->
Accuracy achieved by RBF SVM 0.29279700654817586
Area Under the Curve achieved by RBF SVM 0.5612582781456954
Average precision score, micro-averaged over all classes: 0.15



<--                  Gaussian Process                 -->
Accuracy achieved by Gaussian Process 0.6623012160898035
Area Under the Curve achieved by Gaussian Process 0.33833746394181935
Average precision score, micro-averaged over all classes: 0.59



<--                   Decision Tree                   -->
Accuracy achieved by Decision Tree 0.47801683816651075
Area Under the Curve achieved by Decision Tree 0.3687685369520172
Average precision score, micro-averaged over all classes: 0.30



<--                   Random Forest                   -->
Accuracy achieved by Random Forest 0.21047708138447146
Area Under the Curve achieved by Random Forest 0.47636750226844893
Average precision score, micro-averaged over all classes: 0.15



<--                     Neural Net                    -->
Accuracy achieved by Neural Net 0.7623947614593077
Area Under the Curve achieved by Neural Net 0.2639154105553975
Average precision score, micro-averaged over all classes: 0.61



<--                      AdaBoost                     -->
Accuracy achieved by AdaBoost 0.5884003741814781
Area Under the Curve achieved by AdaBoost 0.27484798006473543
Average precision score, micro-averaged over all classes: 0.46



<--                    Naive Bayes                    -->
```

```
Accuracy achieved by Naive Bayes 0.6548175865294668
Area Under the Curve achieved by Naive Bayes 0.3162962662007882
Average precision score, micro-averaged over all classes: 0.48



<--                        QDA                        -->
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/discriminant_analysis.py:878:
UserWarning: Variables are collinear
  warnings.warn("Variables are collinear")
```

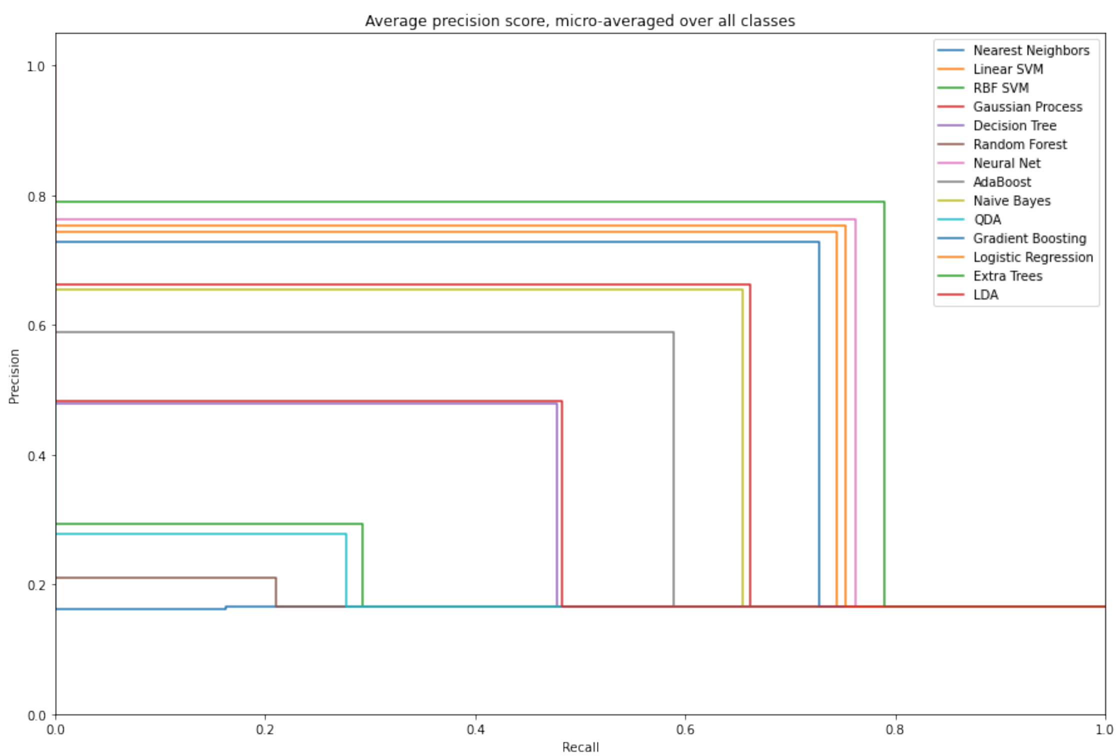
```
Accuracy achieved by QDA 0.2768942937324602
Area Under the Curve achieved by QDA 0.5692147780982949
Average precision score, micro-averaged over all classes: 0.16



<--                 Gradient Boosting                 -->
Accuracy achieved by Gradient Boosting 0.7277829747427502
Area Under the Curve achieved by Gradient Boosting 0.2521228619022468
Average precision score, micro-averaged over all classes: 0.60



<--                Logistic Regression                -->
Accuracy achieved by Logistic Regression 0.7530402245088869
Area Under the Curve achieved by Logistic Regression 0.2639357250233616
Average precision score, micro-averaged over all classes: 0.61



<--                    Extra Trees                    -->
Accuracy achieved by Extra Trees 0.7895229186155285
Area Under the Curve achieved by Extra Trees 0.25116131041861345
Average precision score, micro-averaged over all classes: 0.66



<--                        LDA                        -->
Accuracy achieved by LDA 0.48269410664172124
Area Under the Curve achieved by LDA 0.4633831714947385
Average precision score, micro-averaged over all classes: 0.30
```

On remarque que le modèle avec l'accuracy la plus elevée est Extra Trees avec un précision de 0.79 un avergage precision score 0.66 et un AUC de 0.26.

L'accuracy de la matrice W+I avec Extra Trees est la plus elevée.

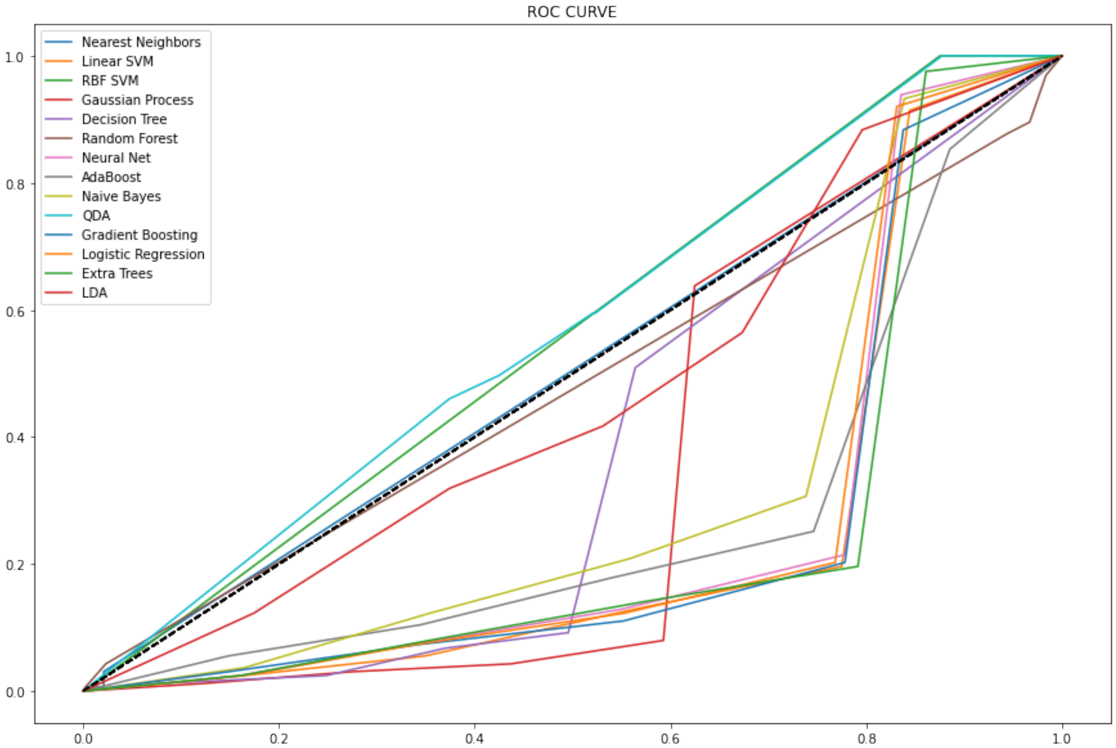
[ ]:
```
plt.figure(figsize=(15,10))
for model in names:
    plt.step(recall_clf[model]['micro'], precision_clf[model]['micro'],␣
 ↪where='post', label=model)
    plt.xlabel('Recall')
    plt.ylabel('Precision')
    plt.ylim([0.0, 1.05])
    plt.xlim([0.0, 1.0])
plt.legend()
plt.title('Average precision score, micro-averaged over all classes')
```

[ ]:
```
Text(0.5, 1.0, 'Average precision score, micro-averaged over all classes')
```



[ ]:
```
plt.figure(figsize=(15,10))
for model in names:
  plt.plot(auc_clf[model]['fpr'], auc_clf[model]['tpr'], label=model)
  plt.plot([0,1], [0,1], 'k--')
plt.legend()
plt.title('ROC CURVE')
```

[ ]:
```
Text(0.5, 1.0, 'ROC CURVE')
```


ROC CURVE
Nearest Neighbors
Linear SVM
RBF SVM
Gaussian Process
Decision Tree
Random Forest
Neural Net
AdaBoost
Naive Bayes
QDA
Gradient Boosting
Logistic Regression
Extra Trees
LDA
0.0
0.2
0.4
0.6
0.8
1.0
0.0
0.2
0.4
0.6
0.8
1.0