2 class models showing actionable variables

September 3, 2018

```
In [11]: from pathlib import Path
         import pandas as pd
         import numpy as np
         from datetime import datetime
         import time
         import matplotlib.pyplot as plt
         %matplotlib inline
         #%pylab inline
         import itertools
         import pickle
         from sklearn.model_selection import train_test_split
         from sklearn.preprocessing import StandardScaler
         from sklearn.linear_model import LogisticRegression
         from sklearn.model_selection import cross_val_score, GridSearchCV
         from sklearn.decomposition import PCA
         from sklearn.ensemble import RandomForestClassifier
         from sklearn.metrics import confusion_matrix, f1_score, precision_score, recall_score
         from sklearn.preprocessing import LabelEncoder
         from sklearn.preprocessing import LabelBinarizer
         from sklearn.preprocessing import OneHotEncoder
         from sklearn.svm import SVC
         from sklearn.model_selection import StratifiedKFold
         from sklearn.feature_selection import RFECV, RFE
         from sklearn.utils import resample
```

```
In [12]: path_project = Path.home() / Path('Google Drive/Felix')
         path_data = path_project / Path("data")
         path_dump = path_project / Path("dump")
```

```
In [13]: # loading data
         file = path_data / Path("dataset.csv")
         with Path.open(file, 'rb') as fp:
             df = pd.read_csv(fp,  encoding='utf-8',low_memory=False, index_col = 0)
```

```
In [14]: # load feature sets
         filename = path_dump / Path("dict_features_sets.sav")
         with open(filename, 'rb') as fp:
              dict_features_sets = pickle.load(fp)
```

```
        usual_common_features = dict_features_sets['usual_common_features']
        indiv_act_features = dict_features_sets['indiv_act_features']
        lasso_20_features = dict_features_sets['lasso_20_features']
```

```
In [15]: scope = lasso_20_features | indiv_act_features
```

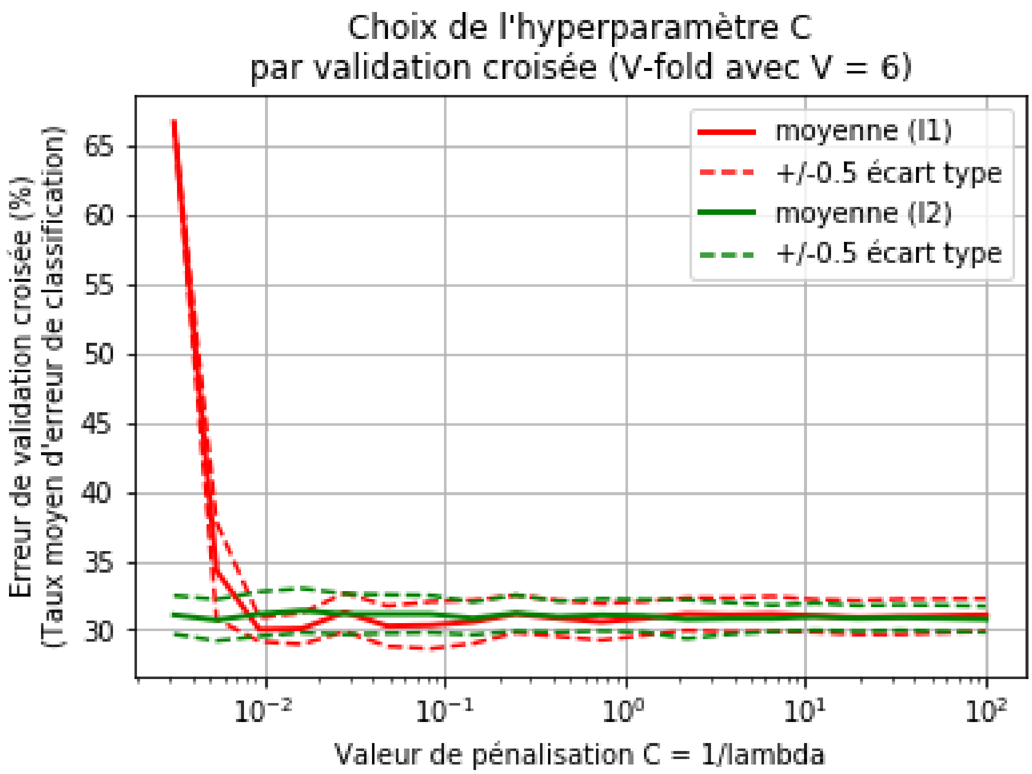
```
In [19]: n_max = 2000

         df_tmp = df.loc[:,lasso_20_features | indiv_act_features | {"HEUREUX_CLF"} ].dropna()

         features = df.loc[:,lasso_20_features | indiv_act_features ].columns

         X = df_tmp.loc[:,lasso_20_features | indiv_act_features]
         y = df_tmp["HEUREUX_CLF"]

         X, y = resample(X, y)

         X = X.iloc[0:n_max,:]
         y = y.iloc[0:n_max]

         X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                             test_size=0.2,
                                                             random_state=42
                                                            )

         scaler = StandardScaler().fit(X_train)
         X_train = scaler.transform(X_train)
         X_test = scaler.transform(X_test)

         print(f"Number exemple: {y.shape[0]}\n- training set: \
         {y_train.shape[0]}\n- test set: {y_test.shape[0]}")
         print(f"Number of features: p={X_train.shape[1]}")
         print(f"Number of class: {len(np.unique(y))}")
         for c in np.unique(y):
             print(f"class {c:0.0f} : {100*np.sum(y==c)/len(y):0.1f}%")
```

```
Number exemple: 2000
- training set: 1600
- test set: 400
Number of features: p=70
Number of class: 2
class 0 : 34.1%
class 1 : 65.9%
```

```
In [40]: nb_value = 20 # Nombre de valeurs testées pour l'hyperparamètre
         mean_score_l1 = np.zeros(nb_value)
         mean_score_l2 = np.zeros(nb_value)
```

```
C_log = np.logspace(-2.5,2,nb_value)
cv = 6 # V-fold, nombre de fold

mean_score_l1 = np.empty(nb_value)
std_scores_l1 = np.empty(nb_value)

mean_score_l2 = np.empty(nb_value)
std_scores_l2 = np.empty(nb_value)

np.random.seed(seed=42)

startTime = time.time()

for i, C in enumerate(C_log):
    clf = LogisticRegression(C=C, penalty='l1',
                             tol=0.01, random_state=42,
                             class_weight='balanced')
    mean_score_l1[i] = 100*np.mean(1-cross_val_score(clf,
                                                     X_train,
                                                     y_train,
                                                     cv=cv,
                                                     scoring='accuracy'))
    std_scores_l1[i] = 100*np.std(1-cross_val_score(clf,
                                                    X_train,
                                                    y_train,
                                                    cv=cv,
                                                    scoring='accuracy'))


for i, C in enumerate(C_log):
    clf = LogisticRegression(C=C, penalty='l2', tol=0.01, random_state=42, class_weight
    mean_score_l2[i] = 100*np.mean(1-cross_val_score(clf,
                                                     X_train,
                                                     y_train,
                                                     cv=cv,
                                                     scoring='accuracy'))
    std_scores_l2[i] = 100*np.std(1-cross_val_score(clf,
                                                    X_train,
                                                    y_train,
                                                    cv=cv,
                                                    scoring='accuracy'))

plt.figure()
plt.semilogx(C_log,mean_score_l1[:],'r',linewidth=2,label='moyenne (l1)')
plt.semilogx(C_log,mean_score_l1[:]-0.5*std_scores_l1[:],
             'r--', label=u'+/-0.5 écart type')
plt.semilogx(C_log,mean_score_l1[:]+0.5*std_scores_l1[:],'r--')
```

```
plt.semilogx(C_log,mean_score_l2[:],'g',linewidth=2,label='moyenne (l2)')
plt.semilogx(C_log,mean_score_l2[:]-0.5*std_scores_l2[:], 'g--', label=u'+/-0.5 écart t
plt.semilogx(C_log,mean_score_l2[:]+0.5*std_scores_l2[:],'g--')

plt.xlabel("Valeur de pénalisation C = 1/lambda")
plt.ylabel(u"Erreur de validation croisée (%)\n(Taux moyen d'erreur de classification)"
plt.title(u"Choix de l'hyperparamètre C\npar validation croisée \
(V-fold avec V = %s)" % (cv))
plt.legend(bbox_to_anchor=(1, 1))
plt.grid()
plt.show()
print("Détermination des paramètres optimaux en %0.1f s" % (time.time() - startTime))
print("Pénalisation l1, valeur optimale : C = %0.2f" % (C_log[np.argmin(mean_score_l1)]
print("Pénalisation l2, valeur optimale : C = %0.2f" % (C_log[np.argmin(mean_score_l2)]
```




```
Détermination des paramètres optimaux en 12.5 s
Pénalisation l1, valeur optimale : C = 0.01
Pénalisation l2, valeur optimale : C = 0.01
```

In [41]:
```
# Learning on full training set with optimals hyperparameters
# and score evaluation on test set
```

```
        clf = LogisticRegression(C=C_log[np.argmin(mean_score_l1)],
                                 penalty='l1',
                                 random_state=42,
                                 class_weight='balanced')
        clf.fit(X_train, y_train)
        y_test_pred = clf.predict(X_test)
        accuracy = clf.score(X_test, y_test)
        print(f"Model score\n- Accuracy : {accuracy*100:0.1f} %")
        f1 = f1_score(y_test, y_test_pred)
        p = precision_score(y_test, y_test_pred)
        r = recall_score(y_test, y_test_pred)
        print(f"- Precision : {p*100:0.1f} % (Happy # positive class)")
        print(f"- Recall : {r*100:0.1f} %")
        print(f"- F1 score : {f1*100:0.1f} %")
```

```
Model score
- Accuracy : 73.0 %
- Precision : 78.2 % (Happy # positive class)
- Recall : 78.8 %
- F1 score : 78.5 %
```

```
In [42]: # Learning on full training set with optimals hyperparameters
         # and score evaluation on test set
         clf = LogisticRegression(C=C_log[np.argmin(mean_score_l2)],
                                  penalty='l2',
                                  random_state=42,
                                  class_weight='balanced')
         clf.fit(X_train, y_train)
         y_test_pred = clf.predict(X_test)
         accuracy = clf.score(X_test, y_test)
         print(f"Model score\n- Accuracy : {accuracy*100:0.1f} %")
         f1 = f1_score(y_test, y_test_pred)
         p = precision_score(y_test, y_test_pred)
         r = recall_score(y_test, y_test_pred)
         print(f"- Precision : {p*100:0.1f} % (Happy # positive class)")
         print(f"- Recall : {r*100:0.1f} %")
         print(f"- F1 score : {f1*100:0.1f} %")
```

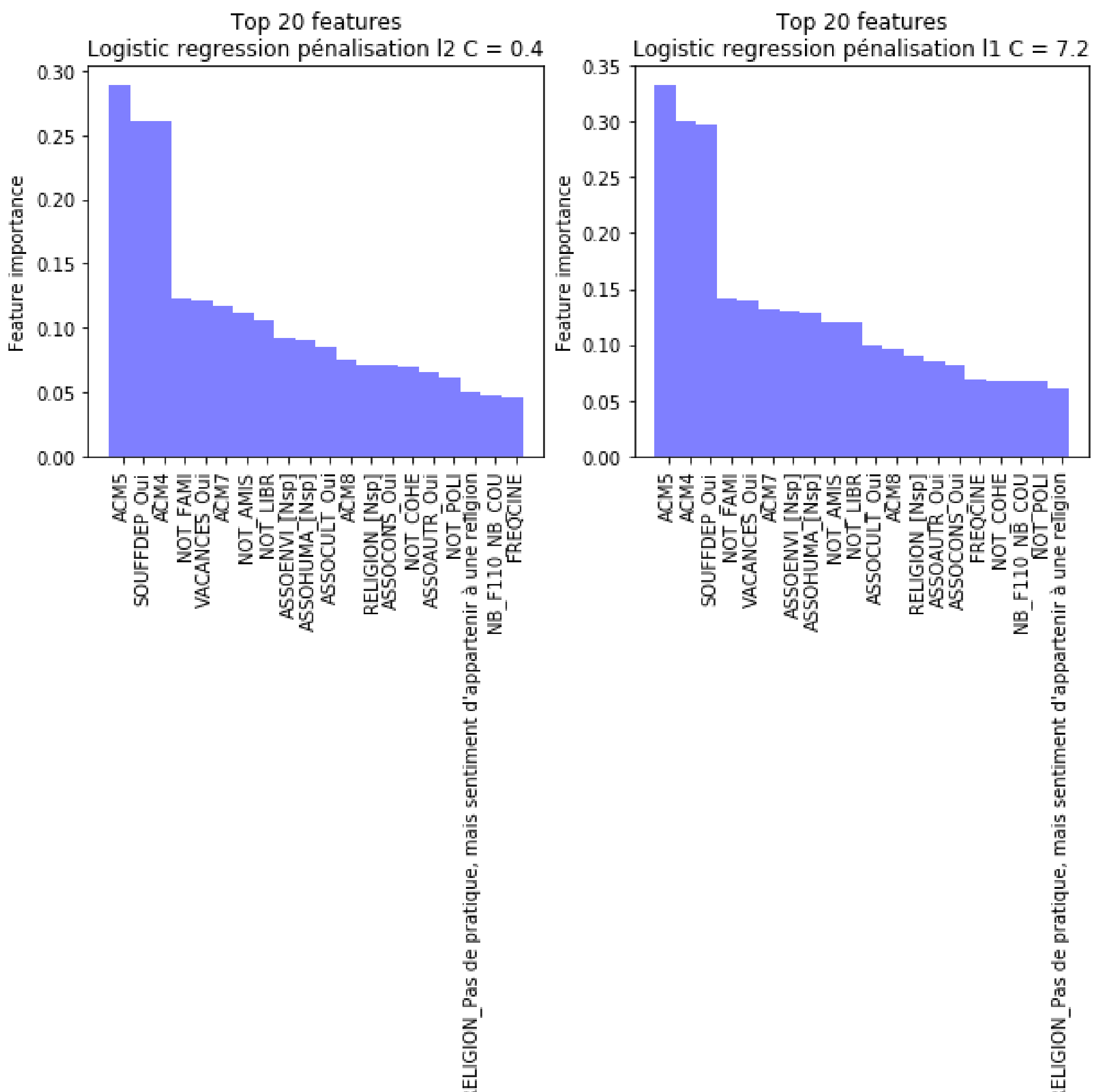
```
Model score
- Accuracy : 71.5 %
- Precision : 80.4 % (Happy # positive class)
- Recall : 72.0 %
- F1 score : 75.9 %
```

```
In [79]: features = df_tmp.columns.drop(["HEUREUX_CLF"])
         # Use regression coefficients to rank features
         clf = LogisticRegression(C=C_log[np.argmin(mean_score_l2)],
```

```
                                penalty='l2',
                                random_state=42,
                                class_weight='balanced')


    clf.fit(X_train,y_train)
    coef_l2 = abs(clf.coef_)
    coef_sorted_l2 = -np.sort(-coef_l2).reshape(-1)
    print(coef_sorted_l2)
    features_sorded_l2 = np.argsort(-coef_l2).reshape(-1)
    print(features_sorded_l2)
    features_name = np.array(features)
    features_name_sorted_l2 = features_name[features_sorded_l2]

    clf = LogisticRegression(C=C_log[np.argmin(mean_score_l1)],
                                penalty='l2',
                                random_state=42,
                                class_weight='balanced')

    clf.fit(X_train,y_train)
    coef_l1 = abs(clf.coef_)
    coef_sorted_l1 = -np.sort(-coef_l1).reshape(-1)
    features_sorded_l1 = np.argsort(-coef_l1).reshape(-1)
    features_name_sorted_l1 = features_name[features_sorded_l1]

    nf = min(X_train.shape[1],20)

    fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(10, 4))
    ind = np.arange(nf)     # the x locations for the groups

    plt.subplot(1, 2, 1)
    p1 = plt.bar(ind, coef_sorted_l2[0:nf], 1, color='b',alpha=0.5)
    plt.ylabel('Feature importance')
    plt.title(u'Top %i features\nLogistic regression pénalisation l2 C = 0.4' % nf)
    plt.xticks(ind + 0.35/2.0, features_name_sorted_l2[0:nf], rotation = 90)

    plt.subplot(1, 2, 2)
    p1 = plt.bar(ind, coef_sorted_l1[0:nf], 1, color='b',alpha=0.5)
    plt.ylabel('Feature importance')
    plt.title(u'Top %i features\nLogistic regression pénalisation l1 C = 7.2' % nf)
    plt.xticks(ind + 0.35/2.0, features_name_sorted_l1[0:nf], rotation = 90)

    plt.show()
```

```
[ 0.28918924  0.26094902  0.26035124  0.12293843  0.12056448  0.11758471
  0.11086364  0.10571498  0.0924942   0.09031865  0.08520895  0.07534933
  0.07161449  0.0712178   0.06972505  0.06504603  0.06105644  0.05013991
  0.04785051  0.04574973  0.04030477  0.03818504  0.03548995  0.03470828
```

```
  0.03459128  0.03333439  0.03064415  0.02742764  0.0272144   0.0265467
  0.02586892  0.02541776  0.02531397  0.02171971  0.02116637  0.01990121
  0.01915592  0.01895105  0.01879546  0.018207    0.0178006   0.01762086
  0.01719412  0.01668544  0.01498402  0.01450985  0.01359048  0.012893
  0.00999465  0.00838993  0.00746007  0.0073291   0.00504336  0.00388026
  0.00331852  0.00290678  0.002556    0.00247781  0.          0.          0.
  0.          0.          0.          0.          0.          0.          0.
  0.          0.        ]
[57 43 55  8 15 28 65 25 27 48 61 39 44  2 60 59 41  3 16 53 68 17 62 20  5
 12 69 14 22 66 18  4  9 33 37 23  0 13 26 24 46 31 56 40 52 49 63 45 47 19
  7 64 34 67 42 21  6 10  1 38 32 36 11 30 58 29 50 54 51 35]
```




```
In [58]: set(features_name_sorted_l1) - scope
```

Out[58]: set()

In [75]:
```
for i,feature in enumerate(features_name_sorted_l1):
    if i < 20:
        if feature in indiv_act_features:
            print(f"acionate {feature}, {coef_l1[abs(coef_l1) == coef_sorted_l1[i]][0]:
```

```
acionate NOT_FAMI, 0.1410
acionate VACANCES_Oui, 0.1394
acionate ASSOENVI_[Nsp], 0.1302
acionate ASSOHUMA_[Nsp], 0.1276
acionate NOT_AMIS, 0.1209
acionate NOT_LIBR, 0.1203
acionate ASSOCULT_Oui, 0.1001
acionate RELIGION_[Nsp], 0.0892
acionate ASSOAUTR_Oui, 0.0853
acionate ASSOCONS_Oui, 0.0816
acionate FREQCINE, 0.0681
acionate NOT_COHE, 0.0680
acionate NOT_POLI, 0.0667
acionate RELIGION_Pas de pratique, mais sentiment d'appartenir à une religion, 0.0601
```

In [81]:
```
startTime = time.time()
n_estimators_range = [32,64,128,256,512]
max_depth_range = [4,8,16,32,64]
param_grid = dict(n_estimators=n_estimators_range, max_depth = max_depth_range)

params = {'max_features' :'sqrt', 'random_state' : 32,
          'min_samples_split' : 2, 'class_weight' : 'balanced'}
clf = RandomForestClassifier(**params)

grid = GridSearchCV(clf, scoring='accuracy', param_grid=param_grid)
grid.fit(X_train, y_train)
print(f"Determination of optimal hyperparameters in {time.time() - startTime:0.1f} s")
print(f"Optimal values are {grid.best_params_} \n\
Accuracy Score of cross valdation {100*grid.best_score_:0.2f}%")

# Learning on full training set with optimals hyperparameters and score on test set
params = {'max_features' :'sqrt', 'random_state' : 32,
          'min_samples_split' : 2, 'class_weight' : 'balanced',
          'n_estimators' : grid.best_params_['n_estimators'],
          'max_depth' : grid.best_params_['max_depth']}
clf = RandomForestClassifier(**params).fit(X_train, y_train)
clf.fit(X_train, y_train)
y_test_pred = clf.predict(X_test)

print(f"Random Forest, p={X_train.shape[1]}")
```

```
        accuracy = clf.score(X_test, y_test)
        f1 = f1_score(y_test, y_test_pred)
        p = precision_score(y_test, y_test_pred)
        r = recall_score(y_test, y_test_pred)
        print(f"Model score\n- Accuracy : {accuracy*100:0.1f} %")
        print(f"- Precision : {p*100:0.1f} % (Happy # positive class)")
        print(f"- Recall : {r*100:0.1f} %")
        print(f"- F1 score : {f1*100:0.1f} %")
```

```
Determination of optimal hyperparameters in 52.0 s
Optimal values are {'max_depth': 32, 'n_estimators': 256}
Accuracy Score of cross valdation 73.81%
Random Forest, p=70
Model score
- Accuracy : 72.0 %
- Precision : 70.9 % (Happy # positive class)
- Recall : 93.6 %
- F1 score : 80.7 %
```

In [82]:
```
# loading cdv data
file = path_data / Path("clustTest1.csv")
with Path.open(file, 'rb') as fp:
    clustTest1 = pd.read_csv(fp,  encoding='utf-8',low_memory=False, sep=";", index_col
```

In [84]:
```
#score = dict()

n_estimators_range = [16,32,64,128]
max_depth_range = [2,4,8,16,32,64]
param_grid = dict(n_estimators=n_estimators_range, max_depth = max_depth_range)
params = {'max_features' :'sqrt',
          'random_state' : 32,
          'min_samples_split' : 2,
          'class_weight' : 'balanced'
         }

score_clustering_methods = []
clustering_methods = clustTest1.columns[0:3]

for method in clustering_methods:
    print(f"\nAnalysis cluster method {method}")
    cluster_list = clustTest1[method].unique()
    print(f"liste of clusters : {cluster_list}")
    score_cluster = []
    for cluster in cluster_list:
        index_scope = clustTest1.loc[clustTest1[method]==cluster,:].index
        print(f"cluster {cluster} : {len(index_scope)} elements")
```

```python
# treating remaining missing values
n_max = 2000
df_tmp = df.loc[:,lasso_20_features | indiv_act_features | {"HEUREUX_CLF"} ].dr
features = df.loc[:,lasso_20_features | indiv_act_features ].columns

X = df_tmp.loc[:,lasso_20_features | indiv_act_features]
y = df_tmp["HEUREUX_CLF"]

X, y = resample(X, y)

X = X.iloc[0:n_max,:]
y = y.iloc[0:n_max]

X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size=0.2,
                                                    random_state=42)

scaler = StandardScaler().fit(X_train)
X_train = scaler.transform(X_train)
X_test = scaler.transform(X_test)



print(f"Number exemple: {y.shape[0]}\n\
- training set: {y_train.shape[0]}\n\
- test set: {y_test.shape[0]}")
print(f"Number of features: p={X_train.shape[1]}")
print(f"Number of class: {len(np.unique(y))}")
for c in np.unique(y):
    print(f"class {c:0.0f} : {100*np.sum(y==c)/len(y):0.1f}%")


startTime = time.time()
clf = RandomForestClassifier(**params)
grid = GridSearchCV(clf,
                    scoring='accuracy',
                    param_grid=param_grid)

grid.fit(X_train, y_train)
print(f"Optimal values are {grid.best_params_} \n\
Score of cross valdation {100*grid.best_score_:0.2f}%")

# Learning on full training set with optimals hyperparameters and score on test
params_opt = {'max_features' :'sqrt', 'random_state' : 32,
              'min_samples_split' : 2, 'class_weight' : 'balanced',
              'n_estimators' : grid.best_params_['n_estimators'],
              'max_depth' : grid.best_params_['max_depth']}
clf = RandomForestClassifier(**params_opt).fit(X_train, y_train)
```

```
            y_test_pred = clf.predict(X_test)
            accuracy = clf.score(X_test, y_test)
            f1 = f1_score(y_test, y_test_pred)
            p = precision_score(y_test, y_test_pred)
            r = recall_score(y_test, y_test_pred)

            res  = {'f1_score' : f1,
                    'accuracy' : accuracy,
                    'precision' : p,
                    'recall' : r}

            cl = {'cluster' : cluster,
                  'model' : 'RandomForestClassifier',
                  'params' : params_opt,
                  'metrics' : res
                 }

            score_cluster.append(cl)

        d = {'clustering_method' : method,
             'cluster_scores' : score_cluster
            }
        score_clustering_methods.append(d)
```

```
Analysis cluster method clust1
liste of clusters : [1 2 3 4 5 6]
cluster 1 : 295 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 35.4%
class 1 : 64.7%
Optimal values are {'max_depth': 16, 'n_estimators': 128}
        Score of cross valdation 71.56%
cluster 2 : 1729 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 35.5%
class 1 : 64.5%
Optimal values are {'max_depth': 32, 'n_estimators': 64}
```

```
        Score of cross valdation 74.81%
cluster 3 : 3633 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 35.4%
class 1 : 64.7%
Optimal values are {'max_depth': 32, 'n_estimators': 128}
        Score of cross valdation 73.31%
cluster 4 : 218 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 35.0%
class 1 : 65.0%
Optimal values are {'max_depth': 32, 'n_estimators': 128}
        Score of cross valdation 73.38%
cluster 5 : 137 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 36.0%
class 1 : 64.0%
Optimal values are {'max_depth': 32, 'n_estimators': 128}
        Score of cross valdation 73.31%
cluster 6 : 24 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 36.0%
class 1 : 64.0%
Optimal values are {'max_depth': 16, 'n_estimators': 64}
        Score of cross valdation 73.31%

Analysis cluster method clust2
liste of clusters : [4 6 5 1 3 2 7]
cluster 4 : 212 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
```

```
Number of features: p=70
Number of class: 2
class 0 : 34.4%
class 1 : 65.6%
Optimal values are {'max_depth': 32, 'n_estimators': 64}
        Score of cross valdation 73.38%
cluster 6 : 1137 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 32.8%
class 1 : 67.2%
Optimal values are {'max_depth': 16, 'n_estimators': 128}
        Score of cross valdation 74.06%
cluster 5 : 750 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 34.9%
class 1 : 65.1%
Optimal values are {'max_depth': 32, 'n_estimators': 128}
        Score of cross valdation 75.12%
cluster 1 : 1257 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 35.7%
class 1 : 64.3%
Optimal values are {'max_depth': 16, 'n_estimators': 128}
        Score of cross valdation 72.19%
cluster 3 : 1254 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 34.8%
class 1 : 65.2%
Optimal values are {'max_depth': 32, 'n_estimators': 128}
        Score of cross valdation 73.44%
cluster 2 : 857 elements
Number exemple: 2000
```

```
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 34.5%
class 1 : 65.5%
Optimal values are {'max_depth': 32, 'n_estimators': 128}
        Score of cross valdation 74.50%
cluster 7 : 569 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 35.0%
class 1 : 65.0%
Optimal values are {'max_depth': 16, 'n_estimators': 128}
        Score of cross valdation 72.00%

Analysis cluster method clust3
liste of clusters : [5 4 1 2 3]
cluster 5 : 373 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 35.8%
class 1 : 64.2%
Optimal values are {'max_depth': 32, 'n_estimators': 128}
        Score of cross valdation 74.81%
cluster 4 : 2682 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 36.5%
class 1 : 63.5%
Optimal values are {'max_depth': 32, 'n_estimators': 128}
        Score of cross valdation 72.38%
cluster 1 : 1593 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 33.6%
```

```
class 1 : 66.4%
Optimal values are {'max_depth': 16, 'n_estimators': 32}
        Score of cross valdation 74.62%
cluster 2 : 1246 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 35.5%
class 1 : 64.5%
Optimal values are {'max_depth': 16, 'n_estimators': 128}
        Score of cross valdation 74.25%
cluster 3 : 142 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=70
Number of class: 2
class 0 : 34.4%
class 1 : 65.6%
Optimal values are {'max_depth': 8, 'n_estimators': 128}
        Score of cross valdation 73.69%
```

In [87]:
```
#print(f"F1 on full dataset : {100*score_rf['f1_macro']:0.1f}%")
for score_method in score_clustering_methods:
    print(f"method {score_method['clustering_method']}:")
    average_score = 0
    for i, score_cluster in enumerate(score_method['cluster_scores']):
        print(f"cluster {score_cluster['cluster']}, f1 macro {100*score_cluster['metric
        average_score = average_score + score_cluster['metrics']['f1_score']
    average_score = average_score / (i+1)
    print(f"average f1 on clusters {100*average_score:0.1f}%")
```

```
method clust1:
cluster 1, f1 macro 83.8%
cluster 2, f1 macro 79.2%
cluster 3, f1 macro 80.8%
cluster 4, f1 macro 82.7%
cluster 5, f1 macro 80.8%
cluster 6, f1 macro 82.8%
average f1 on clusters 81.7%
method clust2:
cluster 4, f1 macro 82.8%
cluster 6, f1 macro 84.8%
cluster 5, f1 macro 80.9%
cluster 1, f1 macro 82.5%
```

```
cluster 3, f1 macro 83.5%
cluster 2, f1 macro 86.9%
cluster 7, f1 macro 82.1%
average f1 on clusters 83.3%
method clust3:
cluster 5, f1 macro 82.8%
cluster 4, f1 macro 82.0%
cluster 1, f1 macro 82.6%
cluster 2, f1 macro 81.5%
cluster 3, f1 macro 81.9%
average f1 on clusters 82.2%
```