2 class models showing actionable variables

September 3, 2018

In [1]:
```
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 [2]:
```
path_project = Path.home() / Path('Google Drive/Felix')
path_data = path_project / Path("data")
path_dump = path_project / Path("dump")
```

In [3]:
```
# 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 [4]:
```
# 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 [5]:
```
scope = lasso_20_features | indiv_act_features
```

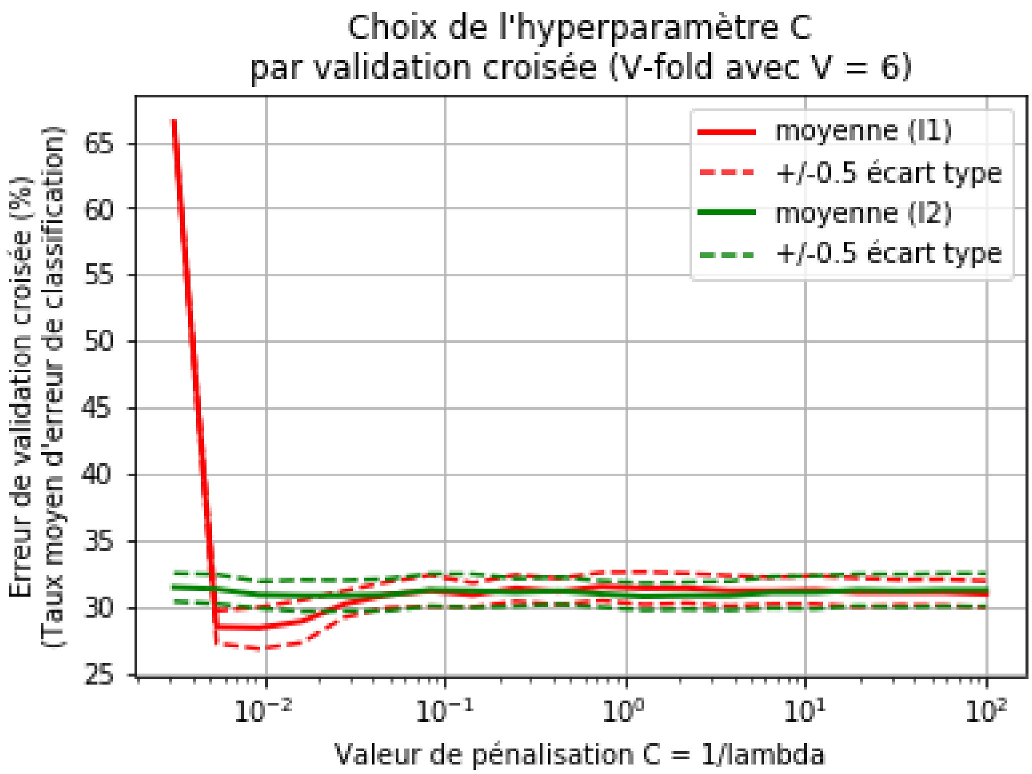
In [6]:
```
n_max = 2000

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 : 65.8%
```

In [7]:
```
nb_value = 20 # Nombre de valeurs testées pour l'hyperparamètre
mean_score_l1 = np.zeros(nb_value)
mean_score_l2 = np.zeros(nb_value)
```

```python
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 ty
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 9.6 s
Pénalisation l1, valeur optimale : C = 0.01
Pénalisation l2, valeur optimale : C = 1.27
```

```
In [8]: # 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} %")
```

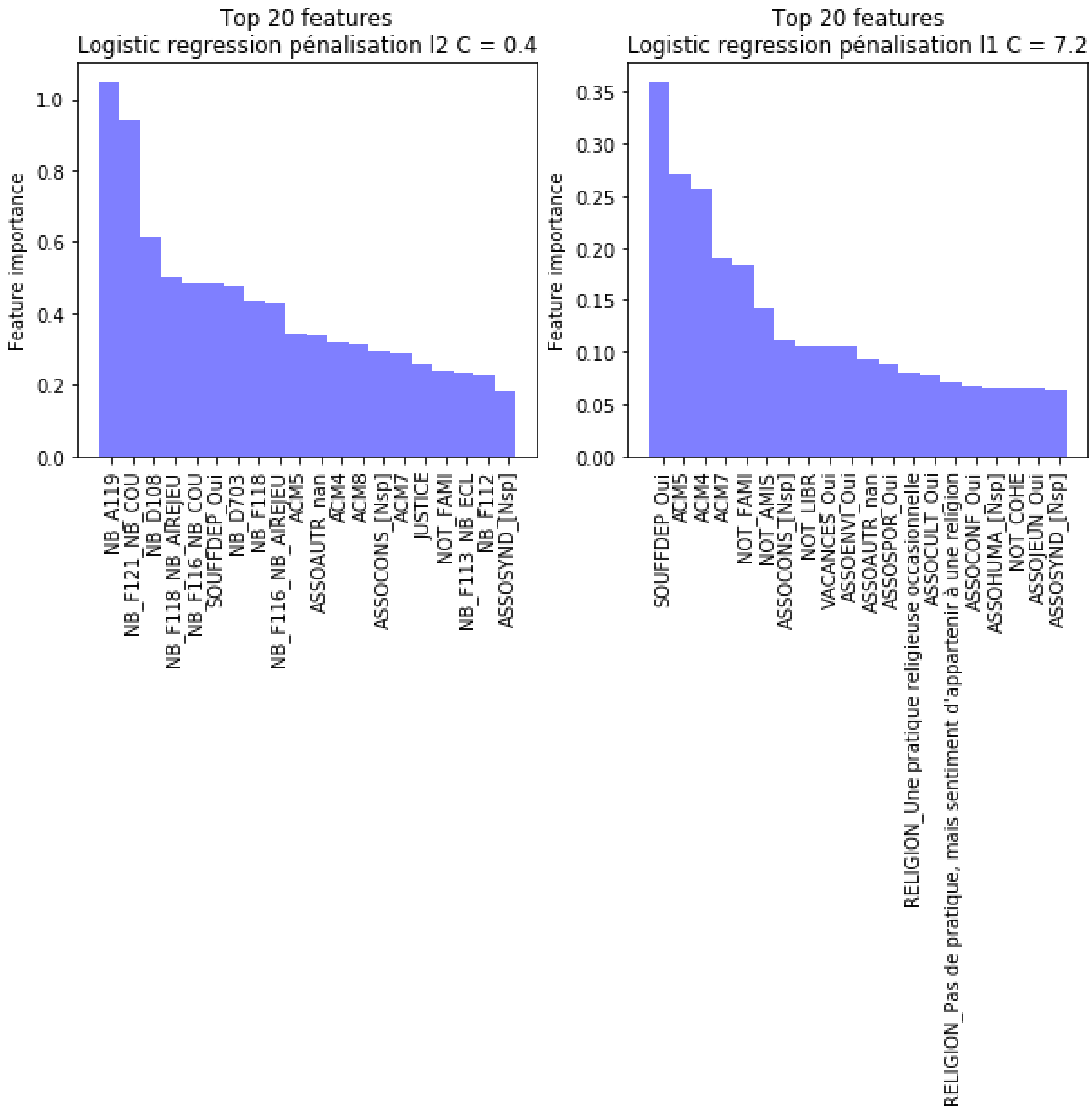
```
Model score
- Accuracy : 73.8 %
- Precision : 78.0 % (Happy # positive class)
- Recall : 81.4 %
- F1 score : 79.7 %
```

In [9]:
```
# 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 : 70.5 %
- Precision : 78.5 % (Happy # positive class)
- Recall : 73.5 %
- F1 score : 75.9 %
```

In [10]:
```
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)
features_sorded_l2 = np.argsort(-coef_l2).reshape(-1)
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()
```




```
In [11]: 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, 0.1837
acionate NOT_AMIS, 0.1428
acionate ASSOCONS_[Nsp], 0.1100
acionate NOT_LIBR, 0.1060
acionate VACANCES_Oui, 0.1057
acionate ASSOENVI_Oui, 0.1052
acionate ASSOAUTR_nan, 0.0932
acionate ASSOSPOR_Oui, 0.0883
```

```
acionate RELIGION_Une pratique religieuse occasionnelle, 0.0803
acionate ASSOCULT_Oui, 0.0771
acionate RELIGION_Pas de pratique, mais sentiment d'appartenir à une religion, 0.0712
acionate ASSOCONF_Oui, 0.0681
acionate ASSOHUMA_[Nsp], 0.0660
acionate NOT_COHE, 0.0659
acionate ASSOJEUN_Oui, 0.0650
acionate ASSOSYND_[Nsp], 0.0645
```

0.0.1 Model valuation on whole scope

In [12]:
```
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 40.2 s
Optimal values are {'max_depth': 32, 'n_estimators': 128}
```

```
Accuracy Score of cross valdation 74.19%
Random Forest, p=70
Model score
- Accuracy : 75.2 %
- Precision : 74.1 % (Happy # positive class)
- Recall : 93.7 %
- F1 score : 82.7 %
```

0.0.2 Model valuation by cluster

```
In [13]: # 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 [14]: #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")

                 # treating remaining missing values
                 n_max = 2000
                 df_tmp = df.loc[index_scope,lasso_20_features | indiv_act_features | {"HEUREUX_
                 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: 266
        - training set: 212
        - test set: 54
Number of features: p=70
Number of class: 2
class 0 : 44.7%
class 1 : 55.3%
Optimal values are {'max_depth': 8, 'n_estimators': 16}
        Score of cross valdation 73.11%
cluster 2 : 1729 elements
Number exemple: 1654
        - training set: 1323
        - test set: 331
Number of features: p=70
Number of class: 2
class 0 : 37.8%
class 1 : 62.2%
Optimal values are {'max_depth': 16, 'n_estimators': 128}
        Score of cross valdation 84.13%
cluster 3 : 3633 elements
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%
```

```
Optimal values are {'max_depth': 16, 'n_estimators': 64}
        Score of cross valdation 78.75%
cluster 4 : 218 elements
Number exemple: 200
        - training set: 160
        - test set: 40
Number of features: p=70
Number of class: 2
class 0 : 27.0%
class 1 : 73.0%
Optimal values are {'max_depth': 16, 'n_estimators': 128}
        Score of cross valdation 81.25%
cluster 5 : 137 elements
Number exemple: 100
        - training set: 80
        - test set: 20
Number of features: p=70
Number of class: 2
class 0 : 51.0%
class 1 : 49.0%
Optimal values are {'max_depth': 2, 'n_estimators': 16}
        Score of cross valdation 77.50%
cluster 6 : 24 elements
Number exemple: 19
        - training set: 15
        - test set: 4
Number of features: p=70
Number of class: 2
class 0 : 63.2%
class 1 : 36.8%
Optimal values are {'max_depth': 2, 'n_estimators': 128}
        Score of cross valdation 66.67%

Analysis cluster method clust2
liste of clusters : [4 6 5 1 3 2 7]
cluster 4 : 212 elements
Number exemple: 189
        - training set: 151
        - test set: 38
Number of features: p=70
Number of class: 2
class 0 : 59.8%
class 1 : 40.2%
Optimal values are {'max_depth': 16, 'n_estimators': 64}
        Score of cross valdation 83.44%
cluster 6 : 1137 elements
Number exemple: 1096
        - training set: 876
```

```
        - test set: 220
Number of features: p=70
Number of class: 2
class 0 : 33.9%
class 1 : 66.1%
Optimal values are {'max_depth': 32, 'n_estimators': 128}
        Score of cross valdation 85.05%
cluster 5 : 750 elements
Number exemple: 724
        - training set: 579
        - test set: 145
Number of features: p=70
Number of class: 2
class 0 : 33.3%
class 1 : 66.7%
Optimal values are {'max_depth': 16, 'n_estimators': 32}
        Score of cross valdation 85.49%
cluster 1 : 1257 elements
Number exemple: 1077
        - training set: 861
        - test set: 216
Number of features: p=70
Number of class: 2
class 0 : 39.6%
class 1 : 60.4%
Optimal values are {'max_depth': 32, 'n_estimators': 64}
        Score of cross valdation 78.75%
cluster 3 : 1254 elements
Number exemple: 1189
        - training set: 951
        - test set: 238
Number of features: p=70
Number of class: 2
class 0 : 33.0%
class 1 : 67.0%
Optimal values are {'max_depth': 32, 'n_estimators': 64}
        Score of cross valdation 84.02%
cluster 2 : 857 elements
Number exemple: 804
        - training set: 643
        - test set: 161
Number of features: p=70
Number of class: 2
class 0 : 31.2%
class 1 : 68.8%
Optimal values are {'max_depth': 16, 'n_estimators': 32}
        Score of cross valdation 84.14%
cluster 7 : 569 elements
```

```
Number exemple: 545
        - training set: 436
        - test set: 109
Number of features: p=70
Number of class: 2
class 0 : 46.6%
class 1 : 53.4%
Optimal values are {'max_depth': 16, 'n_estimators': 128}
        Score of cross valdation 81.19%

Analysis cluster method clust3
liste of clusters : [5 4 1 2 3]
cluster 5 : 373 elements
Number exemple: 361
        - training set: 288
        - test set: 73
Number of features: p=70
Number of class: 2
class 0 : 50.4%
class 1 : 49.6%
Optimal values are {'max_depth': 16, 'n_estimators': 128}
        Score of cross valdation 79.17%
cluster 4 : 2682 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 80.31%
cluster 1 : 1593 elements
Number exemple: 1412
        - training set: 1129
        - test set: 283
Number of features: p=70
Number of class: 2
class 0 : 37.1%
class 1 : 62.9%
Optimal values are {'max_depth': 32, 'n_estimators': 128}
        Score of cross valdation 81.22%
cluster 2 : 1246 elements
Number exemple: 1180
        - training set: 944
        - test set: 236
Number of features: p=70
Number of class: 2
```

```
class 0 : 33.6%
class 1 : 66.4%
Optimal values are {'max_depth': 32, 'n_estimators': 128}
        Score of cross valdation 81.25%
cluster 3 : 142 elements
Number exemple: 104
        - training set: 83
        - test set: 21
Number of features: p=70
Number of class: 2
class 0 : 49.0%
class 1 : 51.0%
Optimal values are {'max_depth': 8, 'n_estimators': 16}
        Score of cross valdation 68.67%
```

In [15]:
```
#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 91.5%
cluster 2, f1 macro 88.9%
cluster 3, f1 macro 86.1%
cluster 4, f1 macro 95.5%
cluster 5, f1 macro 62.5%
cluster 6, f1 macro 66.7%
average f1 on clusters 81.9%
method clust2:
cluster 4, f1 macro 60.9%
cluster 6, f1 macro 89.0%
cluster 5, f1 macro 94.0%
cluster 1, f1 macro 87.2%
cluster 3, f1 macro 89.5%
cluster 2, f1 macro 90.9%
cluster 7, f1 macro 83.1%
average f1 on clusters 84.9%
method clust3:
cluster 5, f1 macro 83.3%
cluster 4, f1 macro 89.0%
cluster 1, f1 macro 88.5%
cluster 2, f1 macro 87.7%
```

```
cluster 3, f1 macro 70.0%
average f1 on clusters 83.7%
```