# Models using full features scope

September 1, 2018

## 1 Firts attempts & Base Model

```
In [48]: 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
```

```
In [49]: path_project = Path.home() / Path('Google Drive/Felix')
         path_data = path_project / Path("data")
         path_dump = path_project / Path("dump")
```

```
In [50]: # loading cdv data
         file = path_data / Path("felix.csv")
         with Path.open(file, 'rb') as fp:
             cdv = pd.read_csv(fp,  encoding='cp1252',low_memory=False, index_col = 0)
```

```
In [51]: # loadind cdv data without format
         file = path_data / Path("felix_ssfmt.csv")
```

```
    with Path.open(file, 'rb') as fp:
        cdv_ssfmt = pd.read_csv(fp,  encoding='cp1252',low_memory=False, index_col = 0)
```

```
In [52]: # loading MergeCommunesEnvi data
         file = path_data / Path("MergeCommunesEnvi.csv")
         with Path.open(file, 'rb') as fp:
             MergeCommunesEnvi = pd.read_csv(fp,  encoding='cp1252',low_memory=False, sep=';', i
```

## 1.1 1) Feature engineering

```
In [53]: filename = path_dump / Path("dict_var_groups.sav")
         with open(filename, 'rb') as fp:
              dict_var_groups = pickle.load(fp)

         scope_2015_var = dict_var_groups['scope_2015_var']
         scope_2016_var = dict_var_groups['scope_2016_var']
         scope_2017_var = dict_var_groups['scope_2017_var']
         scope_2018_var = dict_var_groups['scope_2018_var']
         scope_2015_2018_var = dict_var_groups['scope_2015_2018_var']
         scope_2016_2018_var = dict_var_groups['scope_2016_2018_var']
         scope_2017_2018_var = dict_var_groups['scope_2017_2018_var']
         pred_var = dict_var_groups['pred_var']
         com_var = dict_var_groups['com_var']
         tech_var = dict_var_groups['tech_var']
         text_var = dict_var_groups['text_var']
         bizz_var = dict_var_groups['bizz_var']
         cat_var = dict_var_groups['cat_var']
         cat_max9_var = dict_var_groups['cat_max9_var']
         cat_min10_var = dict_var_groups['cat_min10_var']
         quant_var = dict_var_groups['quant_var']

         indiv_semi_act_var = dict_var_groups["indiv_semi_act_var"]
         indiv_act_var = dict_var_groups["indiv_act_var"]
         admin_semi_act_var = dict_var_groups["admin_semi_act_var"]
         admin_act_var = dict_var_groups["admin_act_var"]
         commune_var = dict_var_groups["commune_var"]
```

```
In [54]: print(f"out of the {MergeCommunesEnvi.shape[1]} variable :")
         print(f"{len(scope_2015_2018_var | commune_var)} variables como, to all years ")
```

```
out of the 571 variable :
486 variables como, to all years
```

```
In [55]: exclusion = com_var | tech_var | bizz_var | text_var
         print(f"Out of the {len(scope_2015_2018_var | commune_var)} variables comon to all year
         print(f"{len(scope_2015_2018_var & exclusion)} are excluded ")
         scope_2015_2018_var_kept = (scope_2015_2018_var | commune_var ) - exclusion
         print(f"{len(scope_2015_2018_var_kept)} are kept ")
```

```
Out of the 486 variables comon to all years
22 are excluded
464 are kept
```

```
In [56]: print(f"out of the {len(scope_2015_2018_var_kept)} common variable :")
         print(f"{len(cat_var & scope_2015_2018_var_kept)} variables are categorial ")
         print(f"{len(quant_var & scope_2015_2018_var_kept)} variables are quantitative ")
```

```
out of the 464 common variable :
171 variables are categorial
290 variables are quantitative
```

```
In [57]: print(f"out of the {len(cat_var & scope_2015_2018_var_kept)} variable categorial:")
         print(f"{len(cat_max9_var & scope_2015_2018_var_kept)} variables have maximum 9 modalit
         print(f"{len(cat_min10_var & scope_2015_2018_var_kept)} variables have more and are exc
         cat_var_kept = cat_max9_var & scope_2015_2018_var_kept
```

```
out of the 171 variable categorial:
156 variables have maximum 9 modalities
18 variables have more and are excluded
```

```
In [58]: scope_quant_var = (quant_var & scope_2015_2018_var_kept)
         #quant_null = np.sum(cdv_ssfmt.loc[:,scope_quant_var].isnull())
         quant_null = np.sum(MergeCommunesEnvi.loc[:,scope_quant_var].isnull())
         quant_var_kept = set(quant_null[quant_null < 200].index)
         print(f"out of the {len(scope_quant_var)} quantitatices variables:")
         print(f"{len(quant_var_kept)} have less than 200 missing values and are kept")
```

```
out of the 290 quantitatices variables:
263 have less than 200 missing values and are kept
```

```
In [59]: len(scope)

Out[59]: 419

In [60]: A = cdv_ssfmt.loc[:,scope_2015_2018_var - exclusion].columns

In [61]: len(scope_2015_2018_var - exclusion)

Out[61]: 246

In [70]: "AGEDIP2" in A

Out[70]: True

In [62]: len(A)
```

```
Out[62]: 246

In [63]: len(df.loc[:,scope_2015_2018_var - exclusion].columns)

Out[63]: 246

In [67]: df.loc[:,scope_2015_2018_var - exclusion].shape

Out[67]: (11131, 246)

In [68]: cdv_ssfmt.loc[:,scope_2015_2018_var - exclusion].shape

Out[68]: (11131, 246)

In [82]: scope = cat_var_kept | quant_var_kept
         MergeCommunesEnvi.loc[:,set(cdv_ssfmt.columns)] = cdv_ssfmt
         df = MergeCommunesEnvi.loc[:,scope]
         #df.loc[:,scope_2015_2018_var - exclusion] = cdv_ssfmt.loc[:,scope_2015_2018_var - excl
         df.loc[:,cat_var_kept - {"HEUREUX"}] = cdv.loc[:,cat_var_kept - {"HEUREUX"}]

In [84]: print(f"Number of variable kept {df.shape[1]}")

Number of variable kept 419
```

### 1.1.1 Encoding 'HEUREUX'

```
In [85]: # reducing problem to a 2 class classification problem
         df["HEUREUX_CLF"] = 0
         df.loc[df["HEUREUX"]==4, "HEUREUX_CLF"] = 1
         df.loc[df["HEUREUX"]==3, "HEUREUX_CLF"] = 1
         df.loc[df["HEUREUX"]==5, "HEUREUX_CLF"] = None

In [86]: # Modelisation as a regression problem
         df["HEUREUX_REG"] = df["HEUREUX"]
         df.loc[df["HEUREUX"]==5, "HEUREUX_REG"] = None
```

### 1.1.2 Encoding categorial variables

```
In [87]: p = df.shape[1]
         print(f"{p} columns")
         print(f"out of which {len(cat_var_kept)-1} are corresponding to categorial features")

421 columns
out of which 155 are corresponding to categorial features

In [88]: df = pd.get_dummies(df,
                             columns=cat_var_kept - {"HEUREUX"},
                             dummy_na = True,
                             drop_first=1)
```

```
In [89]: q = df.shape[1]
         print(f"{q} columns after encoding")
         print(f"{len(cat_var_kept)-1} variables where re-encoded in {len(cat_var_kept)-1+q-p}")
```

```
838 columns after encoding
155 variables where re-encoded in 572
```

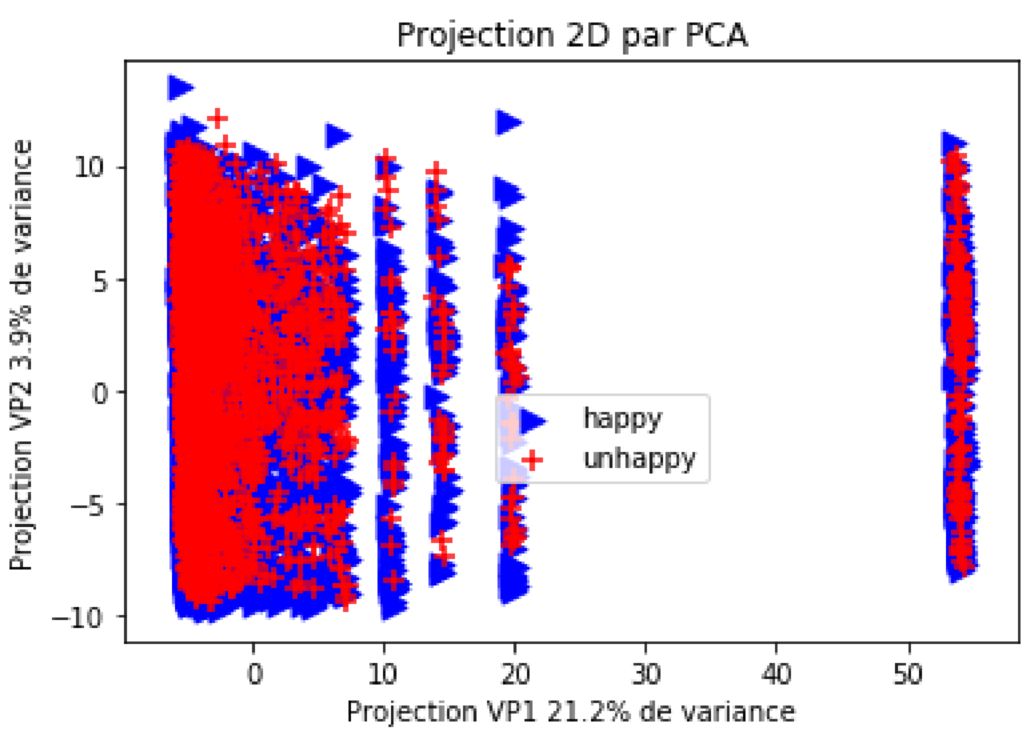
```
In [90]: def get_related_features(variable):
             '''return all columns in global variable df
             starting by variable'''
             if isinstance(variable, str):
                 scope = {variable}
             else:
                 scope = set(variable)
             features = set()
             for element in scope:
                 features = features  | {c for c in df.columns if len(c) > len(element)
                                         and c[0:len(element)] == element
                                         and c[len(element)]=='_'}
             return features
```

## 1.2 2) Dataset construction and visualisation

```
In [91]: # subseting dataframe
         features = df.columns.drop(['HEUREUX',"HEUREUX_CLF", "HEUREUX_REG"])
         pred = "HEUREUX_CLF"

         # treating remaining missing values
         df_tmp = df.loc[:,set(features) | {pred} ].dropna()

         X = df_tmp.loc[:,features]
         y = df_tmp[pred]

         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: 10445
- training set: 8356
- test set: 2089
Number of features: p=835
Number of class: 2
class 0 : 35.1%
class 1 : 64.9%
```

```
In [92]: # Reduction dim PCA
         pca = PCA(n_components=2)
         pca.fit(X_train)
         X_r = pca.transform(X_train)
         happy = (y_train==1)
         unhappy = (y_train==0)
         plt.scatter(X_r[happy,0], X_r[happy,1],
                     s=80, c='blue',marker=">", label="happy")
         plt.scatter(X_r[unhappy,0], X_r[unhappy,1],
                     s=80, c='red',marker='+', label="unhappy")
         plt.ylabel(f'Projection VP2 \
         {pca.explained_variance_ratio_[1]*100:0.1f}% de variance')
         plt.xlabel(f'Projection VP1 \
         {pca.explained_variance_ratio_[0]*100:0.1f}% de variance')
         plt.title("Projection 2D par PCA")
         plt.legend(bbox_to_anchor=(0.4, 0.25))
         plt.show()
```



## 1.3 3) Baseline model

**Logistic regression** with **4 features** to predict a **2 class** variable

### 1.3.1 a) Training set and test set preparation

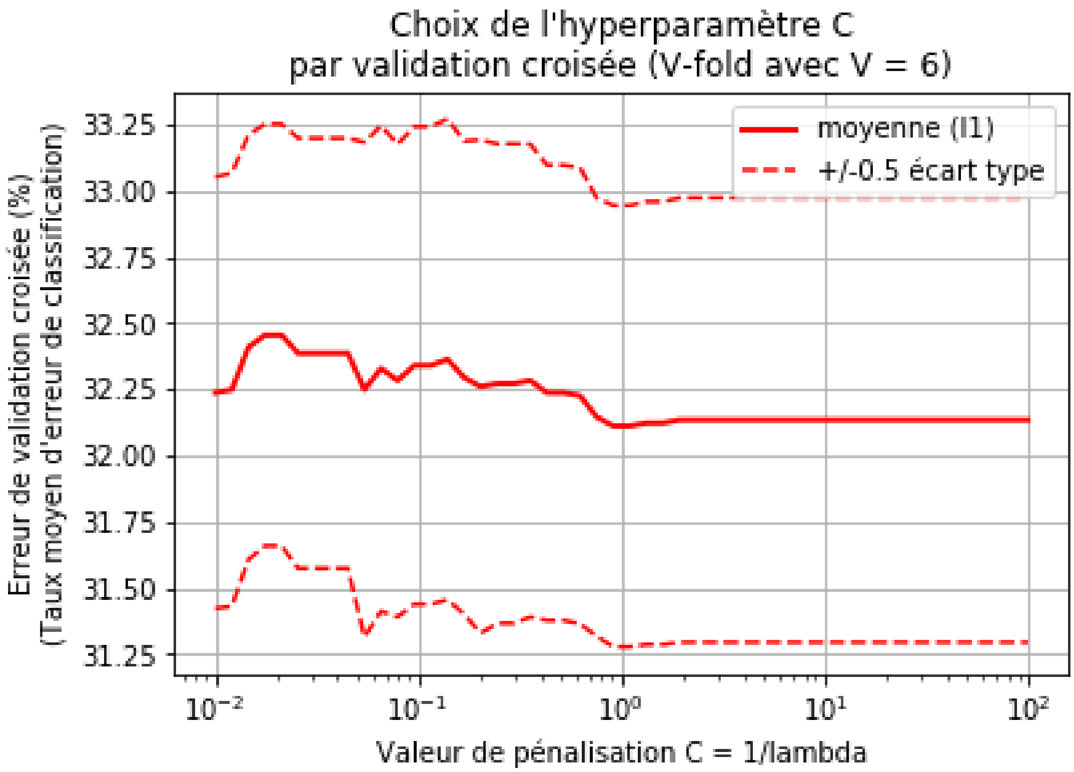
```
In [93]: # subseting dataframe
         features = {'ETATSAN','NOT_AMIS','DEPLOG','NOT_FAMI'}
         pred = "HEUREUX_CLF"

         # treating remaining missing values
         df_tmp = df.loc[:,set(features) | {pred} ].dropna()

         X = df_tmp.loc[:,features]
         y = df_tmp[pred]


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

         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: 10915
- training set: 8732
- test set: 2183
Number of features: p=4
Number of class: 2
class 0 : 34.9%
class 1 : 65.1%
```

### 1.3.2 b) Hyperparameters tuning

```
In [94]: nb_value = 50 # Nombre de valeurs testées pour l'hyperparamètre
         mean_score_l1 = np.zeros(nb_value)
         C_log = np.logspace(-2,2,nb_value)
         cv = 6 # V-fold, nombre de fold

         mean_score_l1 = np.empty(nb_value)
```

```
std_scores_l1 = 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'))




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.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)]
```




```
Détermination des paramètres optimaux en 18.1 s
Pénalisation l1, valeur optimale : C = 0.91
```

### 1.3.3 c) Model training and evaluation

```
In [95]: # 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',
                                  tol=0.01,
                                  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 : 66.6 %
- Precision : 75.9 % (Happy # positive class)
- Recall : 71.5 %
- F1 score : 73.6 %
```

## 1.4 4) Model selection (2 class)

### 1.4.1 a) Finding optimal set of features by recursive elimination using "Lasso" (RFECV)

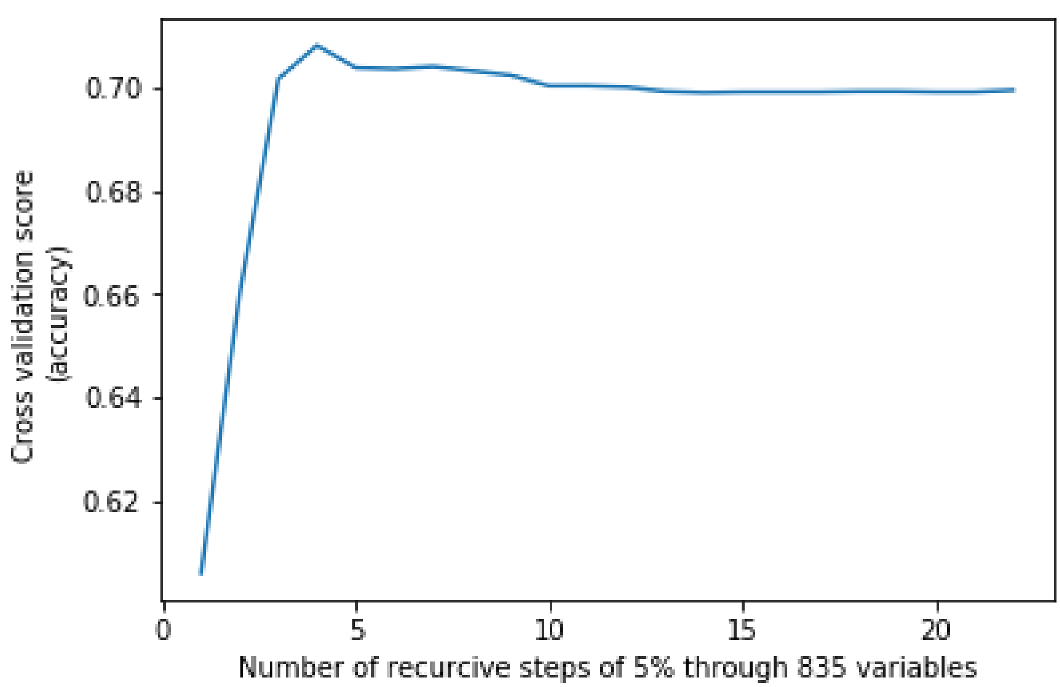
In [96]:
```
# subseting dataframe
features = df.columns.drop(['HEUREUX',"HEUREUX_CLF", "HEUREUX_REG"])
pred = "HEUREUX_CLF"

# treating remaining missing values
print(f"{df.shape[0]} exemples before droping na")
df_tmp = df.loc[:,set(features) | {pred} ].dropna()

X = df_tmp.loc[:,features]
y = df_tmp[pred]

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}%")
```

```
11131 exemples before droping na
Number exemple: 10445
- training set: 8356
- test set: 2089
Number of features: p=835
Number of class: 2
class 0 : 35.1%
class 1 : 64.9%
```

In [97]:
```
startTime = time.time()
```

```
scoring='accuracy'
step = 0.05

clf = LogisticRegression(C=1,
                         penalty='l1',
                         class_weight='balanced',
                         random_state=42)

rfecv = RFECV(estimator=clf, step=step, cv=StratifiedKFold(2),
              scoring=scoring)

rfecv.fit(X_train, y_train)

print("Optimal number of features : %d" % rfecv.n_features_)

# Plot number of features VS. cross-validation scores
plt.figure()
plt.xlabel(f"Number of recurcive steps of {100*step:0.0f}% through {X_train.shape[1]} v
plt.ylabel(f"Cross validation score \n({scoring})")
plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_)
plt.show()
print(f"Détermination des features optimales en %0.1f s" % (time.time() - startTime))
```

```
Optimal number of features : 97
```



```
Détermination des features optimales en 1324.1 s
```

### 1.4.2 b) Using selected features to fit various models

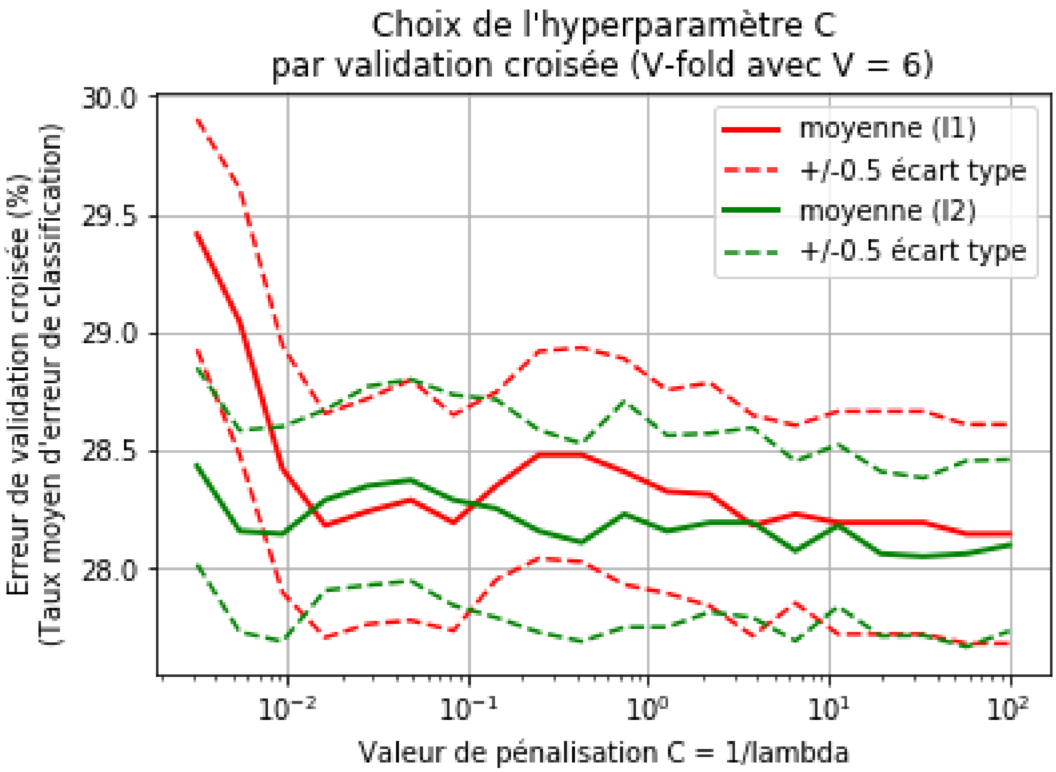
```
In [98]: lasso_mask = rfecv.support_.copy()
         X_train = X_train[:,lasso_mask]
         X_test = X_test[:,lasso_mask]
         print(f"Number of features: p={X_train.shape[1]}")
```

```
Number of features: p=97
```

**Logistic regresion using L1 and L2**

```
In [99]: 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'))
```

```python
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 158.5 s
Pénalisation l1, valeur optimale : C = 57.96
Pénalisation l2, valeur optimale : C = 33.60
```

In [100]:
```python
# 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 : 71.2 %
```

```
- Precision : 81.2 % (Happy # positive class)
- Recall : 72.2 %
- F1 score : 76.4 %
```

In [101]:
```python
# 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 : 71.2 %
- Precision : 81.2 % (Happy # positive class)
- Recall : 72.2 %
- F1 score : 76.4 %
```

**Random Forest**

In [102]:
```python
startTime = time.time()
n_estimators_range = [16,32,64,128]
max_depth_range = [2,4,8,16,32,64,128,256]
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 68.2 s
Optimal values are {'max_depth': 16, 'n_estimators': 128}
Accuracy Score of cross valdation 73.67%
Random Forest, p=97
Model score
- Accuracy : 72.9 %
- Precision : 74.9 % (Happy # positive class)
- Recall : 87.4 %
- F1 score : 80.7 %
```

### 1.4.3 b) Finding optimal set of features of given size by recursive elimination using "Lasso" (RFE)

In [103]:
```
# subseting dataframe
features = df.columns.drop(['HEUREUX',"HEUREUX_CLF", "HEUREUX_REG"])
pred = "HEUREUX_CLF"

# treating remaining missing values
print(f"{df.shape[0]} exemples before droping na")
df_tmp = df.loc[:,set(features) | {pred} ].dropna()

X = df_tmp.loc[:,features]
y = df_tmp[pred]

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}%")
```

```
11131 exemples before droping na
Number exemple: 10445
- training set: 8356
- test set: 2089
Number of features: p=835
Number of class: 2
class 0 : 35.1%
class 1 : 64.9%
```

```
In [104]: startTime = time.time()
          n_features_to_select = 20
          step = 0.05
          clf = LogisticRegression(C=1,
                                   penalty='l1',
                                   class_weight='balanced',
                                   random_state=42)
          selector = RFE(estimator=clf, n_features_to_select=n_features_to_select, step=step)
          selector.fit(X_train, y_train)
          print(f"Optimal support of size {n_features_to_select} found in {time.time() - startTi
```

```
Optimal support of size 20 found in 707.6 s
```

```
In [105]: small_mask = selector.support_.copy()
          X_train = X_train[:,small_mask]
          X_test = X_test[:,small_mask]
          print(f"Number of features: p={X_train.shape[1]}")
```

```
Number of features: p=20
```

```
In [106]: print(f"Selected {X_train.shape[1]} features:\n")
          print(", ".join(X.columns[small_mask]))
```

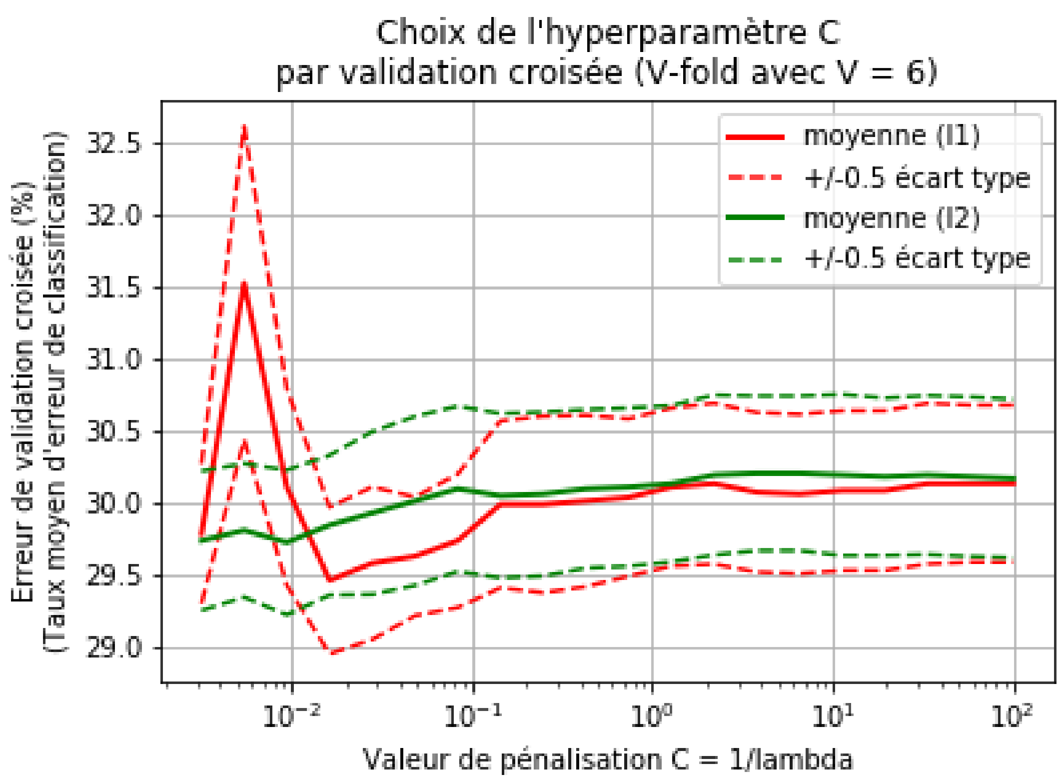
```
Selected 20 features:

NB_F110_NB_COU, ACM8, NB_D703, NB_F116_NB_AIREJEU, CDV5_4, CDV5, ACM4, NB_A119, NB_D108, NB_F113
```

### 1.4.4 c) Using selected features to fit various models

**Logistic regresion using L1 and L2**

```
In [107]: 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_weigh
              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
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 23.7 s
Pénalisation l1, valeur optimale : C = 0.02
```

```
Pénalisation l2, valeur optimale : C = 0.01
```

```
In [108]: # 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 : 69.3 %
- Precision : 77.2 % (Happy # positive class)
- Recall : 74.6 %
- F1 score : 75.9 %
```

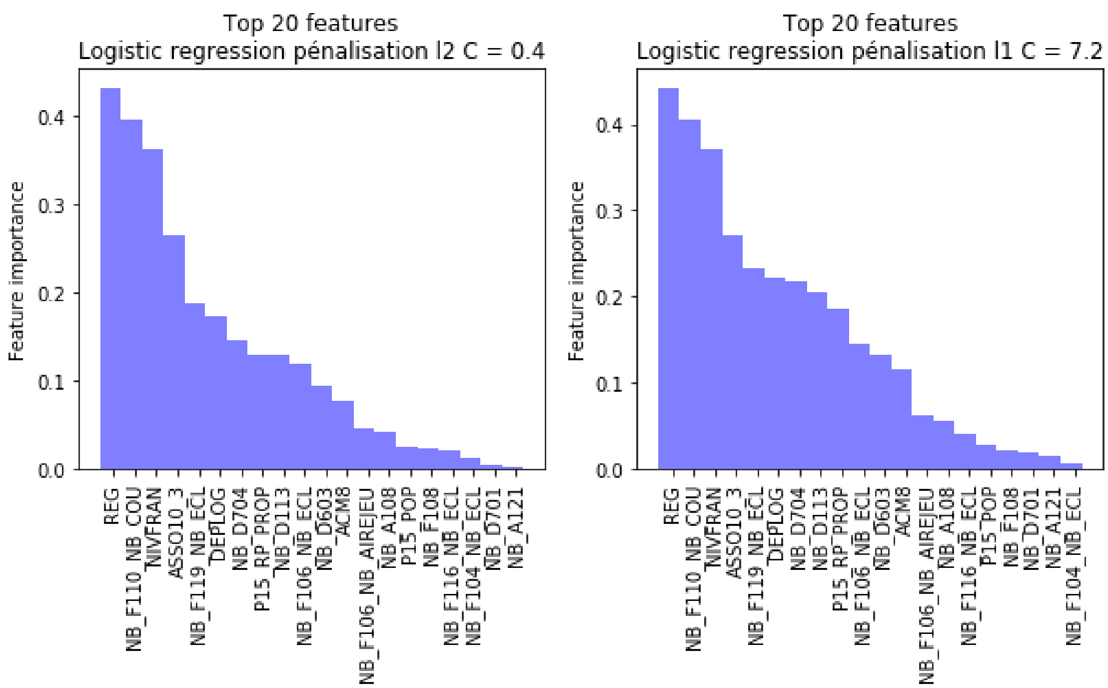
```
In [109]: # Learning on full training set with optimals hyperparameters
          # and score evaluation on test set
          clf = LogisticRegression(C=C_log[np.argmin(mean_score_l2)],
                                   penalty='l2',
                                   random_state=42,
                                   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 : 68.8 %
- Precision : 77.3 % (Happy # positive class)
- Recall : 73.2 %
```

- F1 score : 75.2 %

```
In [110]: # 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 = X_train.shape[1]

          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()
```

```
[ 0.43188048  0.39590771  0.36316748  0.26434544  0.18672389  0.17326869
  0.14586713  0.13010624  0.12890138  0.11797334  0.09381592  0.07736235
  0.04593168  0.04160542  0.02385941  0.02214396  0.0206413   0.01215242
  0.00394785  0.00166955]
[19  6 11 15  5  4  1  2 10 14 16 13  0  7  9  3 17 18 12  8]
```




**Random Forest**

In [111]:
```python
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 117.7 s
Optimal values are {'max_depth': 8, 'n_estimators': 32}
Accuracy Score of cross valdation 70.79%
Random Forest, p=20
Model score
- Accuracy : 69.9 %
- Precision : 77.2 % (Happy # positive class)
- Recall : 76.0 %
- F1 score : 76.6 %
```

## 1.5 5) Multi class regression

### 1.5.1 a) Training and test set preparation

```
In [112]: features = df.columns.drop(['HEUREUX',"HEUREUX_CLF", "HEUREUX_REG"])
          pred = "HEUREUX"

          # treating remaining missing values
          df_tmp = df.loc[:,set(features) | {pred} ]
          df_tmp.loc[df_tmp["HEUREUX"]==5,"HEUREUX"]=None
          df_tmp = df_tmp.dropna()

          X = df_tmp.loc[:,features]
          y = df_tmp[pred]

          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: 10445
- training set: 8356
- test set: 2089
Number of features: p=835
Number of class: 4
class 1 : 1.8%
class 2 : 33.3%
class 3 : 49.0%
class 4 : 15.9%
```

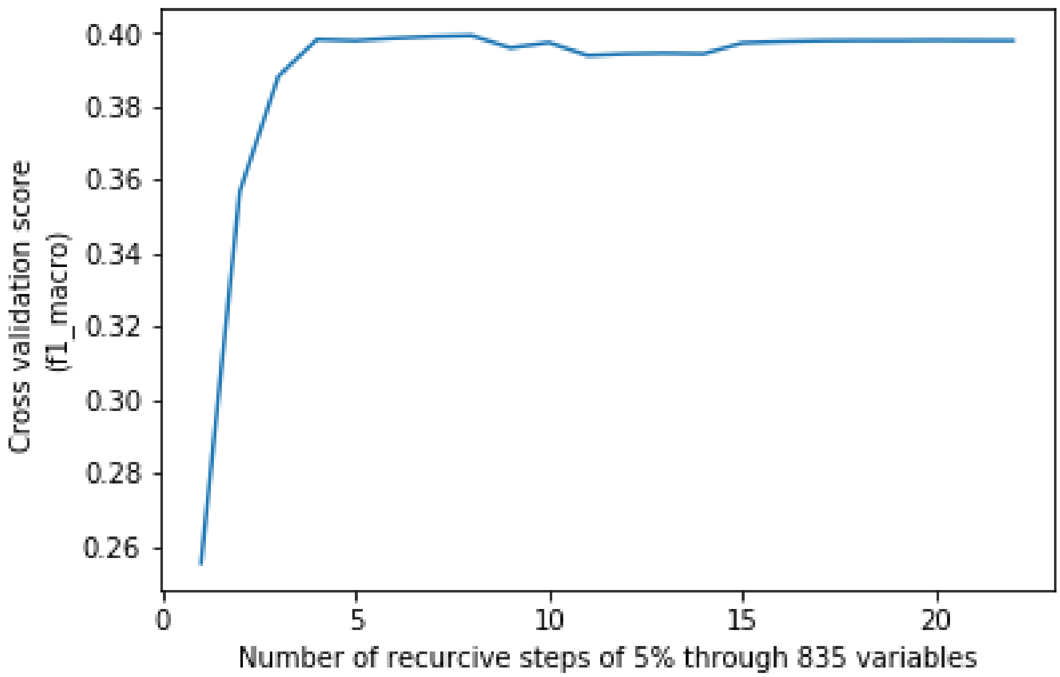
### 1.5.2 b) Feature selection

```
In [113]: startTime = time.time()

          scoring='f1_macro'
          step = 0.05

          clf = LogisticRegression(C=1,
                                   penalty='l1',
                                   class_weight='balanced',
                                   random_state=42)

          rfecv = RFECV(estimator=clf, step=step, cv=StratifiedKFold(2),
                        scoring=scoring)

          rfecv.fit(X_train, y_train)

          print("Optimal number of features : %d" % rfecv.n_features_)

          # Plot number of features VS. cross-validation scores
          plt.figure()
          plt.xlabel(f"Number of recurcive steps of {100*step:0.0f}% through {X_train.shape[1]}
          plt.ylabel(f"Cross validation score \n({scoring})")
          plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_)
          plt.show()
          print(f"Détermination des features optimales en %0.1f s" % (time.time() - startTime))
```

```
//anaconda/envs/py36/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: Undefin
  'precision', 'predicted', average, warn_for)
```

```
//anaconda/envs/py36/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: Undefin
  'precision', 'predicted', average, warn_for)
```

```
Optimal number of features : 261
```




```
Détermination des features optimales en 9491.8 s
```

```
In [114]: nclf_mask = rfecv.support_.copy()
          X_train = X_train[:,nclf_mask]
          X_test = X_test[:,nclf_mask]
          print(f"Number of features: p={X_train.shape[1]}")
```

```
Number of features: p=261
```

```
In [115]: 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(-4,2,nb_value)
          cv = 3 # 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_weigh
    mean_score_l1[i] = 100*np.mean(1-cross_val_score(clf,
                                                     X_train,
                                                     y_train,
                                                     cv=cv,
                                                     scoring='f1_macro'))
    std_scores_l1[i] = 100*np.std(1-cross_val_score(clf,
                                                    X_train,
                                                    y_train,
                                                    cv=cv,
                                                    scoring='f1_macro'))


for i, C in enumerate(C_log):
    clf = LogisticRegression(C=C, penalty='l2', tol=0.01, random_state=42, class_weigh
    mean_score_l2[i] = 100*np.mean(1-cross_val_score(clf,
                                                     X_train,
                                                     y_train,
                                                     cv=cv,
                                                     scoring='f1_macro'))
    std_scores_l2[i] = 100*np.std(1-cross_val_score(clf,
                                                    X_train,
                                                    y_train,
                                                    cv=cv,
                                                    scoring='f1_macro'))

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 type')
plt.semilogx(C_log,mean_score_l2[:]+0.5*std_scores_l2[:],'g--')

plt.xlabel("Valeur de pénalisation C = 1/lambda")
```

```
    plt.ylabel("F1 macro de validation croisée (%)")
    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(f"Détermination des paramètres optimaux en \
    {time.time() - startTime:0.1f} s")
    print(f"Pénalisation l1, valeur optimale : \
    C = {C_log[np.argmax(mean_score_l1)]:0.4f}")
    print(f"Pénalisation l2, valeur optimale : \
    C = {C_log[np.argmax(mean_score_l2)]:0.4f}")
```

```
//anaconda/envs/py36/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: Undefin
  'precision', 'predicted', average, warn_for)
//anaconda/envs/py36/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: Undefin
  'precision', 'predicted', average, warn_for)
//anaconda/envs/py36/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: Undefin
  'precision', 'predicted', average, warn_for)
//anaconda/envs/py36/lib/python3.6/site-packages/sklearn/metrics/classification.py:1135: Undefin
  'precision', 'predicted', average, warn_for)
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```
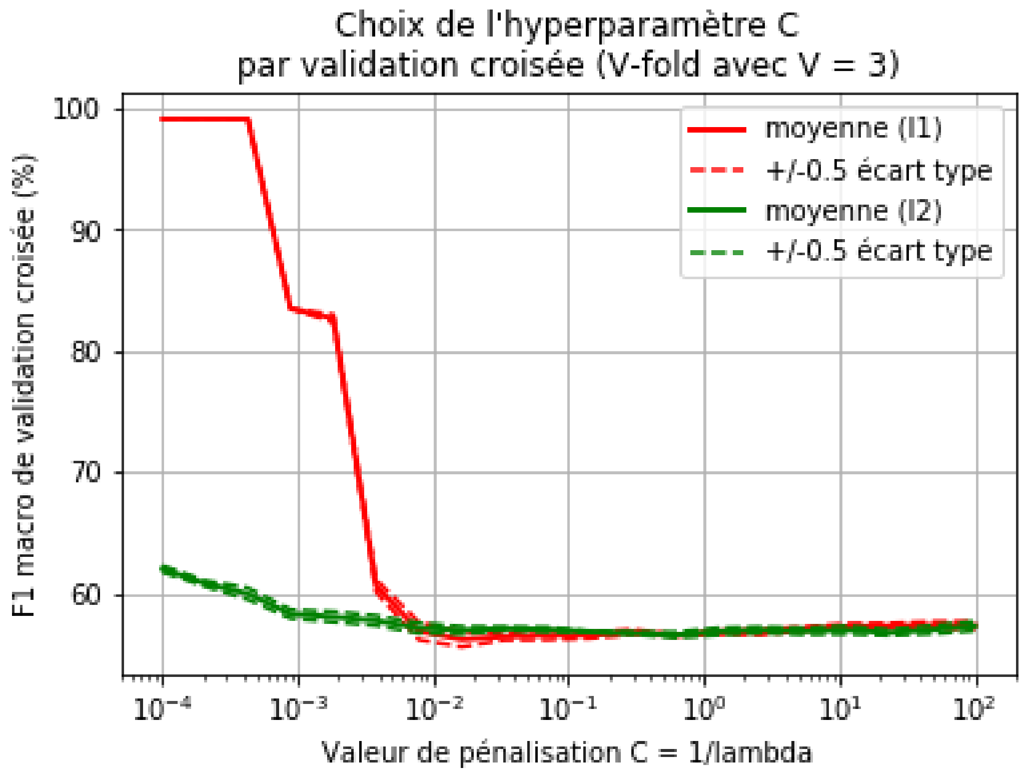




```
Détermination des paramètres optimaux en 2826.3 s
Pénalisation l1, valeur optimale : C = 0.0001
Pénalisation l2, valeur optimale : C = 0.0001
```

```
In [116]: # Learning on full training set with optimals hyperparameters and score on test set
          clf = LogisticRegression(C=C_log[np.argmax(mean_score_l2)],
                                   penalty='l2',
                                   tol=0.01,
                                   random_state=42,
                                   class_weight='balanced')
          clf.fit(X_train, y_train)
          y_test_pred = clf.predict(X_test)
```

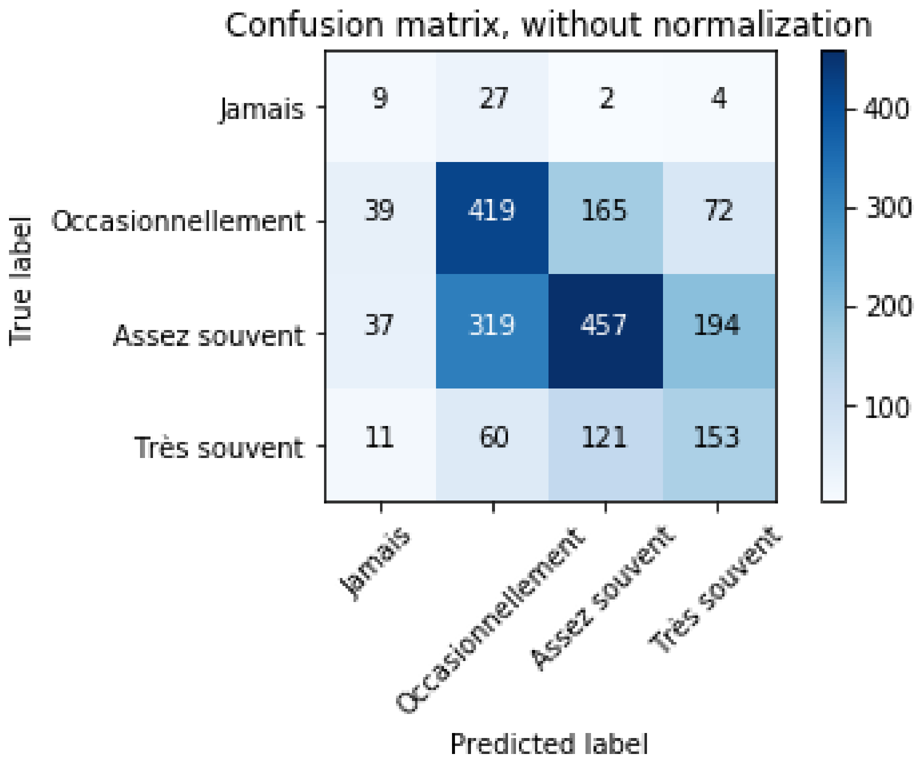
```
In [117]: def plot_confusion_matrix(cm, classes,
                                    normalize=False,
                                    title='Confusion matrix',
                                    cmap=plt.cm.Blues):
              """
              This function prints and plots the confusion matrix.
              Normalization can be applied by setting `normalize=True`.
              """
```

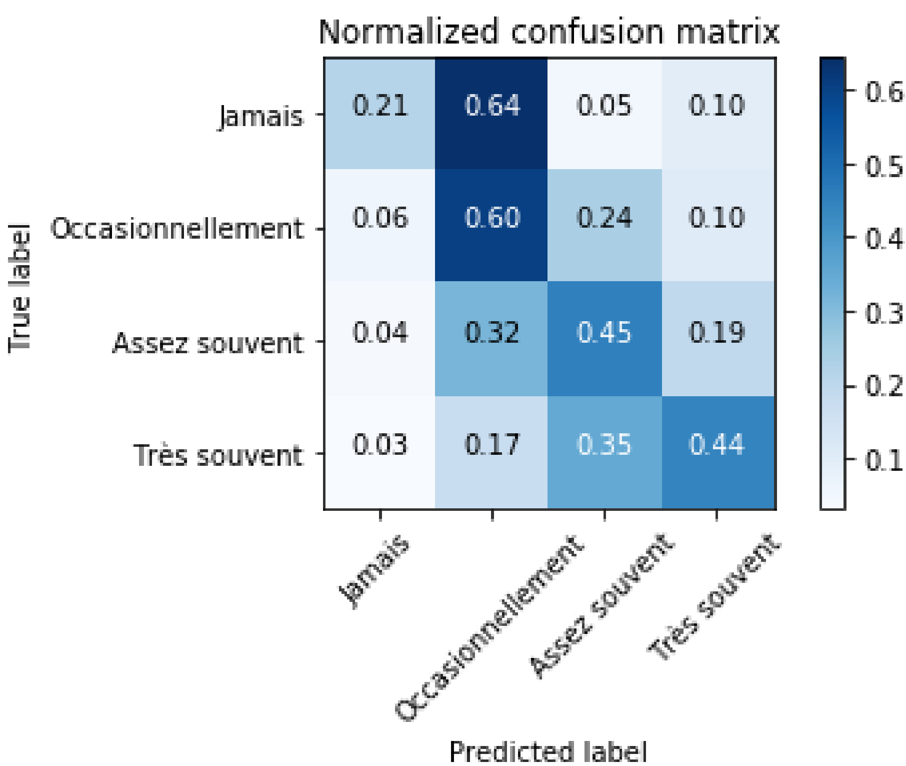
```
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

In [118]:
```
# Model evaluation
class_names = ["Jamais",
               "Occasionnellement",
               "Assez souvent",
               "Très souvent" ]
f1_scores = f1_score(y_test, y_test_pred, labels = [1,2,3,4], average=None)
for i,c in enumerate(class_names):
    print(f"f1 score class '{c}' : {100*f1_scores[i]:0.1f}%")
acurracy = clf.score(X_test, y_test)
f1_macro = f1_score(y_test, y_test_pred, average='macro')
f1_weighted = f1_score(y_test, y_test_pred, average='weighted')
print(f"Average scores :\nf1 macro : {f1_macro*100:0.4f} %\n\
f1 weighted : {f1_weighted*100:0.4f} %\nacurracy : {acurracy*100:0.4f} %")

# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, y_test_pred)
np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names,
                      title='Confusion matrix, without normalization')
```

```python
# Plot normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, normalize=True,
                      title='Normalized confusion matrix')

plt.show()
```

```
f1 score class 'Jamais' : 13.0%
f1 score class 'Occasionnellement' : 55.1%
f1 score class 'Assez souvent' : 52.2%
f1 score class 'Très souvent' : 39.8%
Average scores :
f1 macro : 40.0469 %
f1 weighted : 50.3325 %
acurracy : 49.6888 %
Confusion matrix, without normalization
[[  9  27   2   4]
 [ 39 419 165  72]
 [ 37 319 457 194]
 [ 11  60 121 153]]
Normalized confusion matrix
[[ 0.21  0.64  0.05  0.1 ]
 [ 0.06  0.6   0.24  0.1 ]
 [ 0.04  0.32  0.45  0.19]
 [ 0.03  0.17  0.35  0.44]]
```


Confusion matrix, without normalization
True label
Jamais
Occasionnellement
Assez souvent
Très souvent
9
27
2
4
39
419
165
72
37
319
457
194
11
60
121
153
400
300
200
100
Jamais
Occasionnellement
Assez souvent
Très souvent
Predicted label


Normalized confusion matrix
True label
Jamais
Occasionnellement
Assez souvent
Très souvent
0.21
0.64
0.05
0.10
0.06
0.60
0.24
0.10
0.04
0.32
0.45
0.19
0.03
0.17
0.35
0.44
0.6
0.5
0.4
0.3
0.2
0.1
Jamais
Occasionnellement
Assez souvent
Très souvent
Predicted label