Baseline Model

August 30, 2018

1 Firts attempts & Base Model

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
```

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 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)
```

In [4]:
```
# 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)
```

1.1 1) Feature engineering

```
In [5]: 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']
```

```
In [6]: print(f"out of the {cdv.shape[1]} variable :")
        print(f"{len(scope_2015_2018_var)} variables como, to all years ")
```

```
out of the 354 variable :
268 variables como, to all years
```

```
In [7]: exclusion = com_var | tech_var | bizz_var | text_var
        print(f"Out of the {len(scope_2015_2018_var)} variables comon to all years ")
        print(f"{len(scope_2015_2018_var & exclusion)} are excluded ")
        scope_2015_2018_var_kept = scope_2015_2018_var - exclusion
        print(f"{len(scope_2015_2018_var_kept)} are kept ")
```

```
Out of the 268 variables comon to all years
22 are excluded
246 are kept
```

```
In [8]: 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 246 common variable :
171 variables are categorial
75 variables are quantitative
```

```
In [9]: 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 modaliti
        print(f"{len(cat_min10_var & scope_2015_2018_var_kept)} variables have more and are excl
        cat_var_kept = cat_max9_var & scope_2015_2018_var_kept
```

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

```
In [10]: scope_quant_var = (quant_var & scope_2015_2018_var_kept)
         quant_null = np.sum(cdv_ssfmt.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 75 quantitatices variables:
60 have less than 200 missing values and are kept
```

```
In [11]: scope = cat_var_kept | quant_var_kept
         df = cdv_ssfmt.loc[:,scope]
         df.loc[:,cat_var_kept - {"HEUREUX"}] = cdv.loc[:,cat_var_kept - {"HEUREUX"}]
```

```
In [12]: print(f"Number of variable kept {df.shape[1]}")
```

```
Number of variable kept 216
```

1.1.1 Encoding 'HEUREUX'

```
In [13]: # 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 [14]: # 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 [15]: p = df.shape[1]
         print(f"{p} columns")
         print(f"out of which {len(cat_var_kept)-1} are corresponding to categorial features")
```

```
218 columns
out of which 155 are corresponding to categorial features
```

In [16]:
```
df = pd.get_dummies(df,
                    columns=cat_var_kept - {"HEUREUX"},
                    dummy_na = True,
                    drop_first=1)
```

In [17]:
```
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}")
```

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

In [18]:
```
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
```

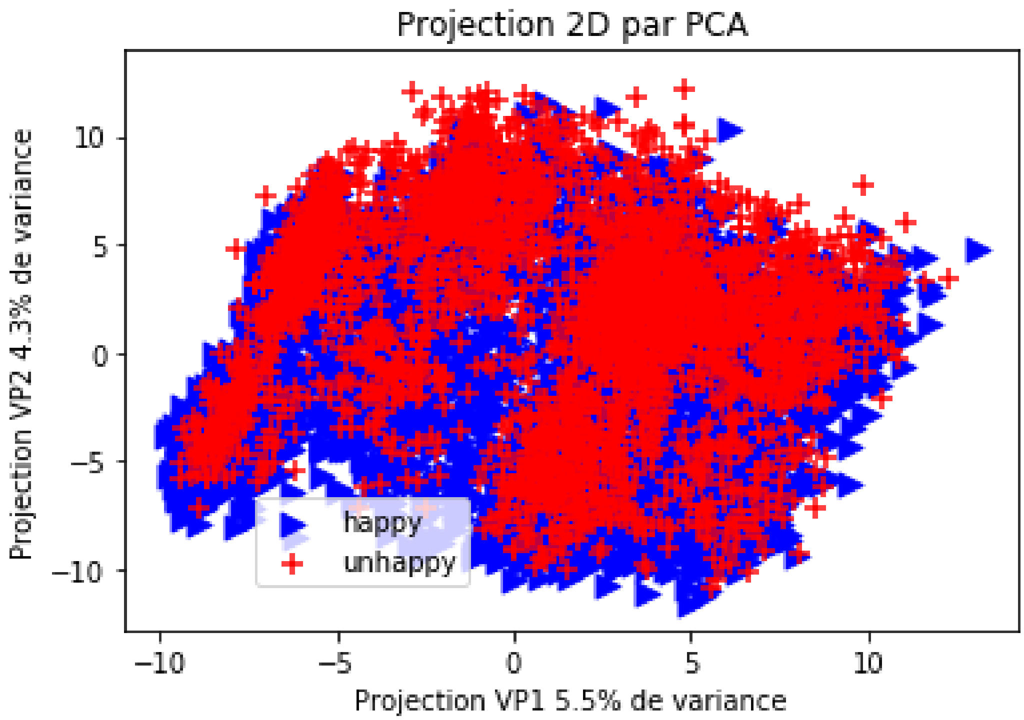
1.2 2) Dataset construction and visualisation

In [19]:
```
# 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]}")
```

```python
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: 10596
- training set: 8476
- test set: 2120
Number of features: p=632
Number of class: 2
class 0 : 34.9%
class 1 : 65.1%
```

In [20]:
```python
# 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 [21]:
```
# 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]}")
```

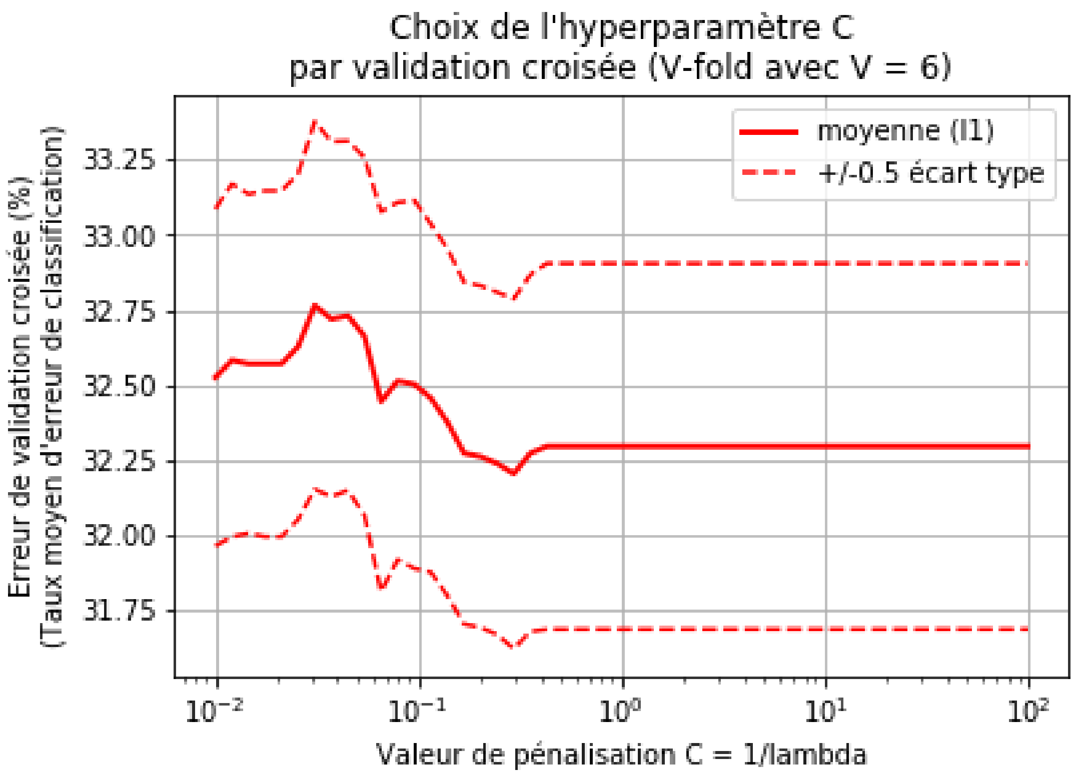
```
print(f"Number of class: {len(np.unique(y))}")
for c in np.unique(y):
    print(f"class {c:0.0f} : {100*np.sum(y==c)/len(y):0.1f}%")
```

```
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 [22]:
```
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 17.5 s
Pénalisation l1, valeur optimale : C = 0.29
```

1.3.3 c) Model training and evaluation

```
In [23]: # 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 : 67.1 %
- Precision : 76.2 % (Happy # positive class)
- Recall : 71.9 %
- F1 score : 74.0 %
```

1.4 4) Model selection (2 class)

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

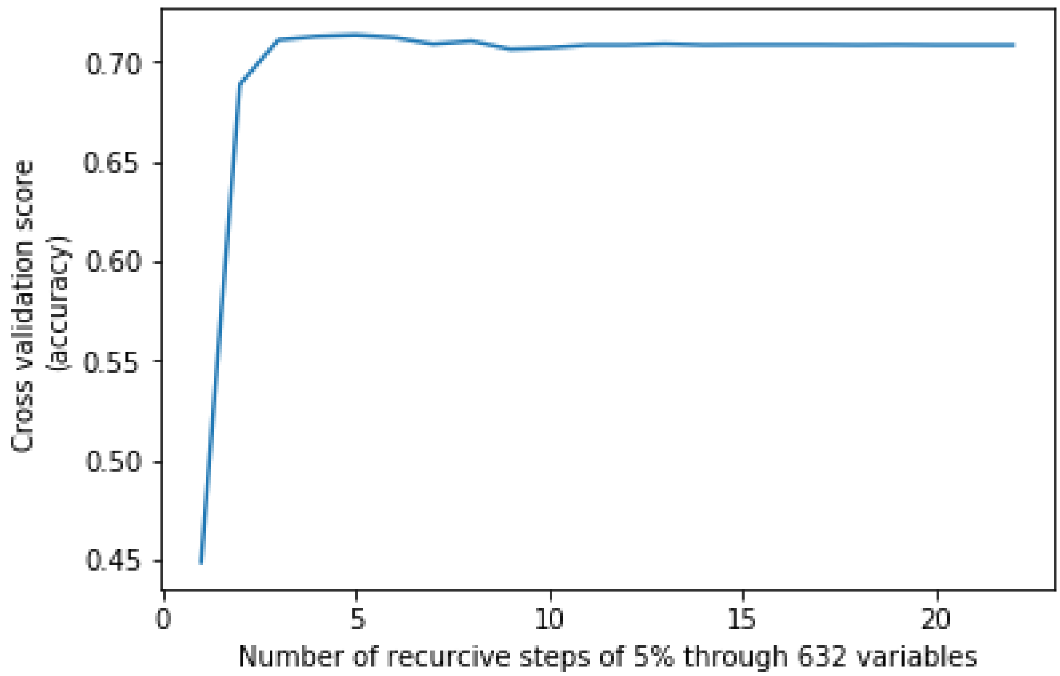
```
In [24]: # subseting dataframe
         features = df.columns.drop(['HEUREUX',"HEUREUX_CLF", "HEUREUX_REG"])
         pred = "HEUREUX_CLF"

         # 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: 10596
- training set: 8476
- test set: 2120
Number of features: p=632
Number of class: 2
class 0 : 34.9%
class 1 : 65.1%
```

```
In [25]: 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 : 105
```




```
Détermination des features optimales en 314.2 s
```

1.4.2 b) Using selected features to fit various models

```
In [26]: 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]}")
```

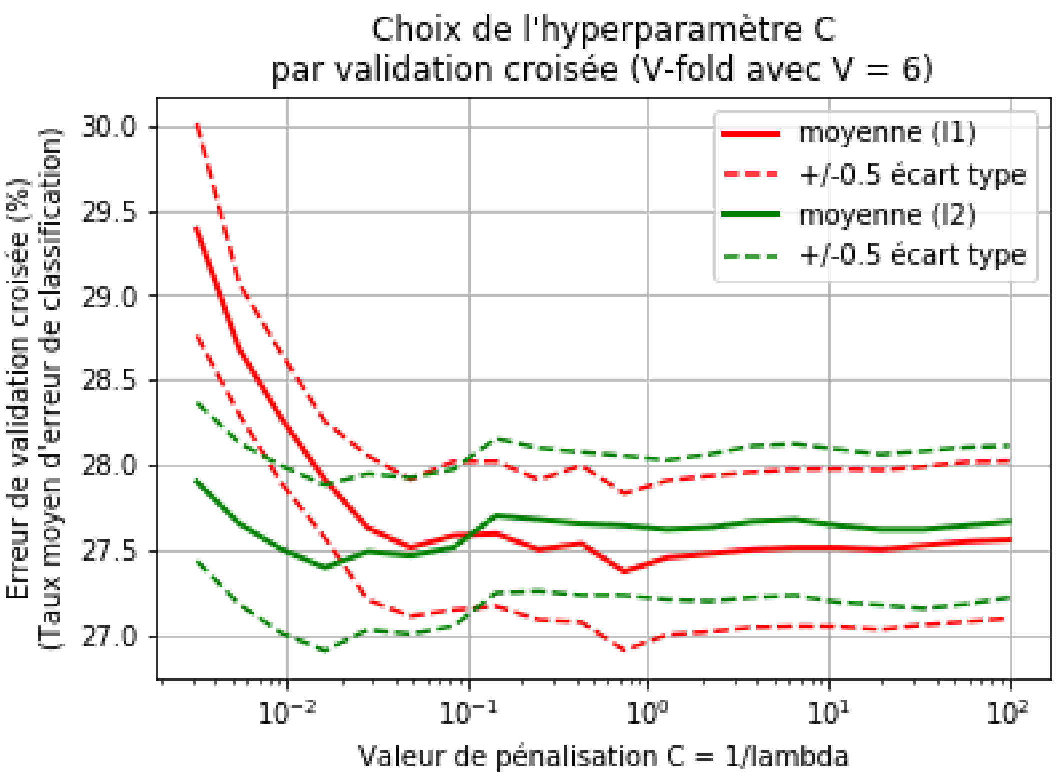
```
Number of features: p=105
```

Logistic regresion using L1 and L2

```
In [27]: 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 109.1 s
Pénalisation l1, valeur optimale : C = 0.74
Pénalisation l2, valeur optimale : C = 0.02
```

In [28]:
```
# 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)
```

```python
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 : 72.0 %
- Precision : 80.4 % (Happy # positive class)
- Recall : 75.3 %
- F1 score : 77.7 %
```

In [29]:
```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 : 72.2 %
- Precision : 80.6 % (Happy # positive class)
- Recall : 75.2 %
- F1 score : 77.8 %
```

Random Forest

In [30]:
```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 75.3 s
Optimal values are {'max_depth': 32, 'n_estimators': 128}
Accuracy Score of cross valdation 73.93%
Random Forest, p=105
Model score
- Accuracy : 73.5 %
- Precision : 74.7 % (Happy # positive class)
- Recall : 89.5 %
- F1 score : 81.4 %
```

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

In [31]:
```
# 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: 10596
- training set: 8476
- test set: 2120
Number of features: p=632
Number of class: 2
class 0 : 34.9%
class 1 : 65.1%
```

```
In [32]: 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() - startTim
```

```
Optimal support of size 20 found in 208.8 s
```

```
In [33]: 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 [34]: print(f"Selected {X_train.shape[1]} features:\n")
         print(", ".join(X.columns[small_mask]))
```

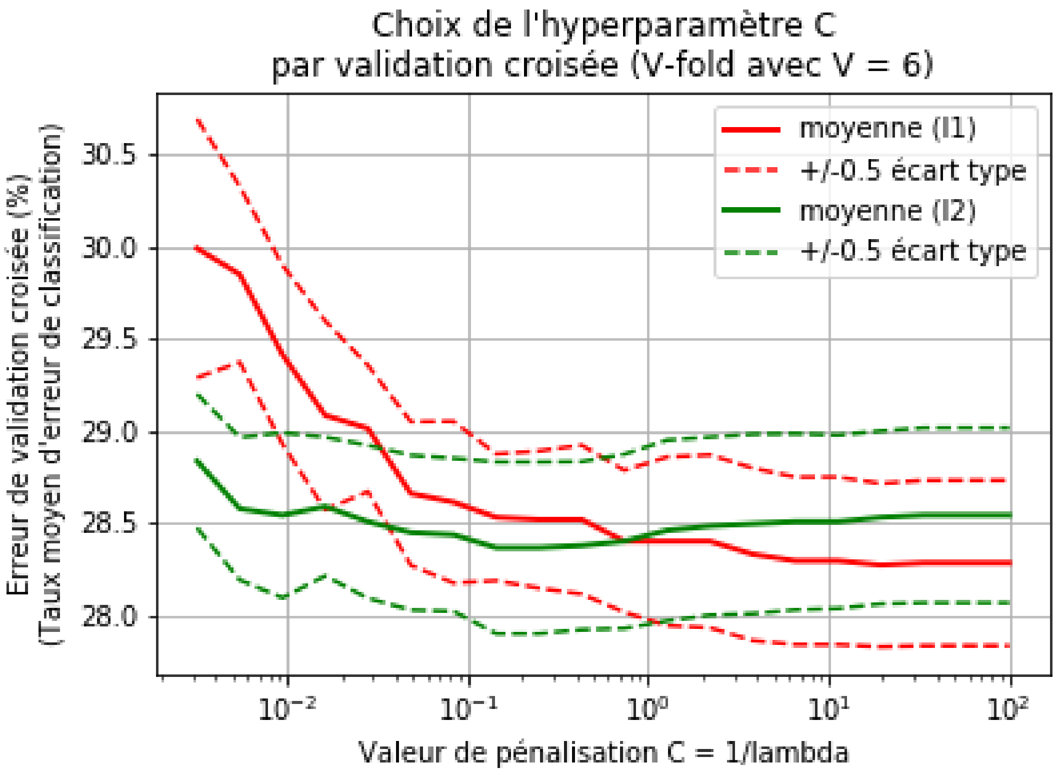
```
Selected 20 features:

ACM8, NIVFRAN, NOT_AMIS, NOT_FAMI, revtot7, ETATSAN, ACM5, NIVPERS0, NIVPERS4, JUSTICE, ACM4, AC
```

1.4.4 c) Using selected features to fit various models

Logistic regresion using L1 and L2

```
In [35]: 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 19.3 s
Pénalisation l1, valeur optimale : C = 19.47
Pénalisation l2, valeur optimale : C = 0.25
```

In [36]:
```
# 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 : 70.6 %
```

```
- Precision : 79.4 % (Happy # positive class)
- Recall : 73.7 %
- F1 score : 76.5 %
```

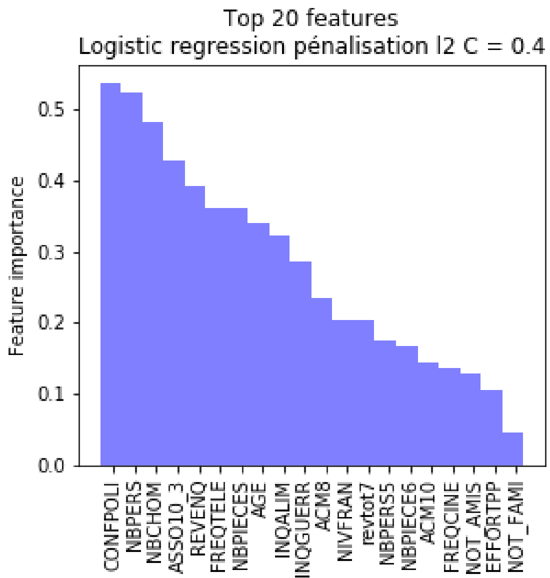
In [37]:
```python
# Learning on full training set with optimals hyperparameters
# and score evaluation on test set
clf = LogisticRegression(C=C_log[np.argmin(mean_score_l2)],
                         penalty='l2',
                         random_state=42,
                         class_weight='balanced')
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} %")
```

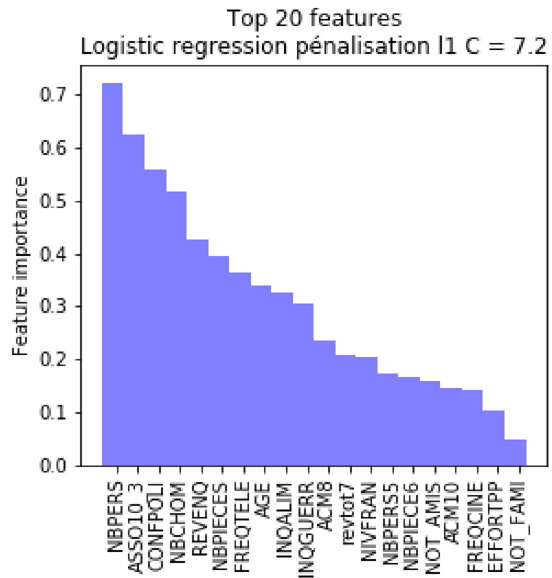
```
Model score
- Accuracy : 70.5 %
- Precision : 79.3 % (Happy # positive class)
- Recall : 73.7 %
- F1 score : 76.4 %
```

In [38]:
```python
# 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()
```

```
[ 0.53592704  0.52387649  0.48346196  0.42868429  0.39190331  0.3607874
  0.36007564  0.33949143  0.32260126  0.28526395  0.23551806  0.20346954
  0.20276202  0.17451806  0.16583378  0.14375142  0.13709309  0.12813629
  0.10392754  0.04596072]
[ 7  1  6 11  0 12  9 13 10  8  2  3 17 18 15 16 19  5  4 14]
```





Random Forest

In [39]:
```
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 141.7 s
Optimal values are {'max_depth': 16, 'n_estimators': 512}
Accuracy Score of cross valdation 71.79%
Random Forest, p=20
Model score
- Accuracy : 71.7 %
- Precision : 75.0 % (Happy # positive class)
- Recall : 84.7 %
- F1 score : 79.5 %
```

1.5 5) Multi class regression

1.5.1 a) Training and test set preparation

In [40]:
```
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}%")
```

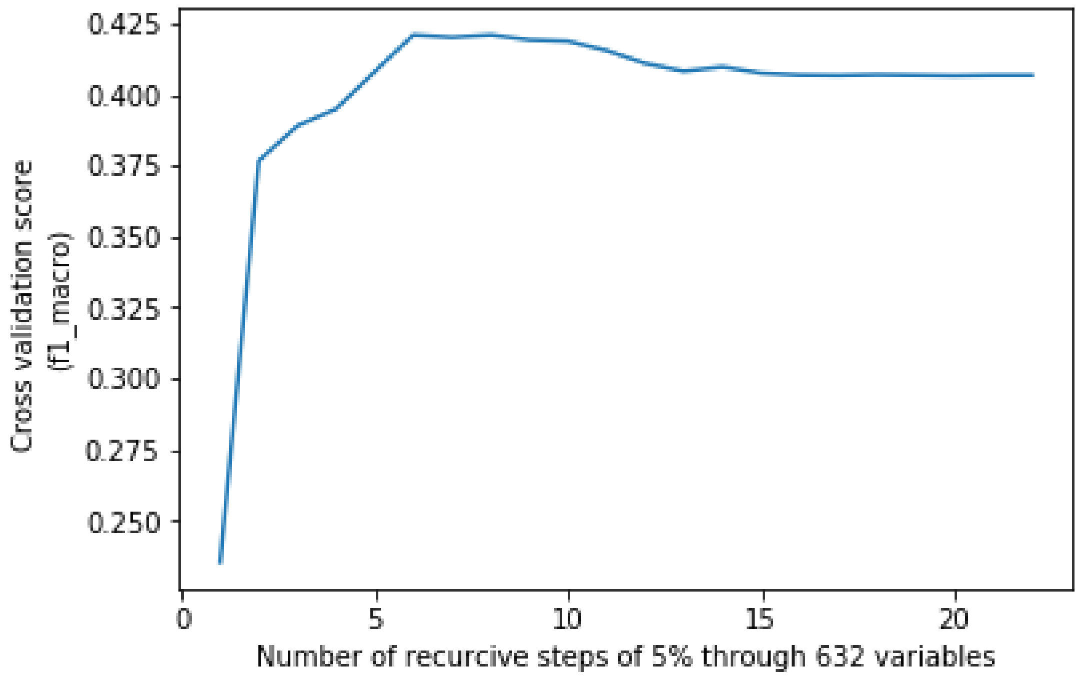
```
Number exemple: 10596
```

```
- training set: 8476
- test set: 2120
Number of features: p=632
Number of class: 4
class 1 : 1.8%
class 2 : 33.1%
class 3 : 49.1%
class 4 : 15.9%
```

1.5.2 b) Feature selection

In [41]:
```
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]} 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))
```

```
//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 : 198
```




```
Détermination des features optimales en 4920.4 s
```

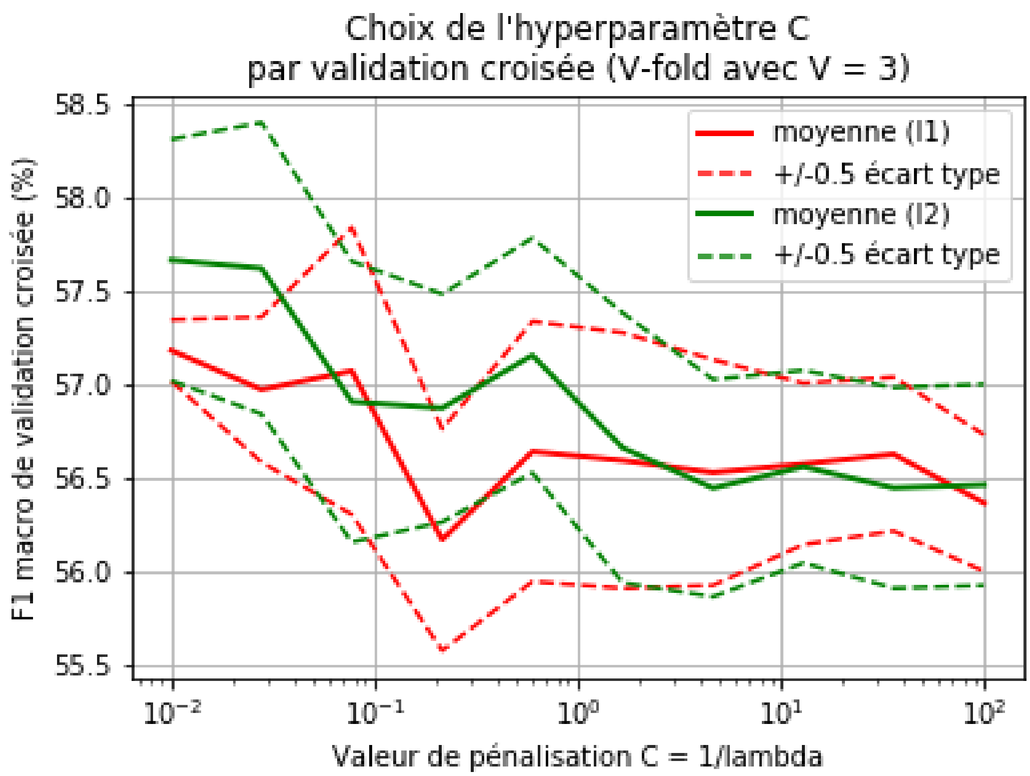
```
In [42]: nclf_mask = rfecv.support_.copy()
         X_train = X_train[:,nclf_mask]
         X_test = X_test[:,nclf_mask]
         print(f"Number of features: p={X_train.shape[1]}")
```

```
Number of features: p=198
```

```
In [43]: nb_value = 10 # 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(-2,2,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_weight
    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_weight
    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}")
```




```
Détermination des paramètres optimaux en 3646.7 s
Pénalisation l1, valeur optimale : C = 0.0100
Pénalisation l2, valeur optimale : C = 0.0100
```

```
In [44]: # 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)
```

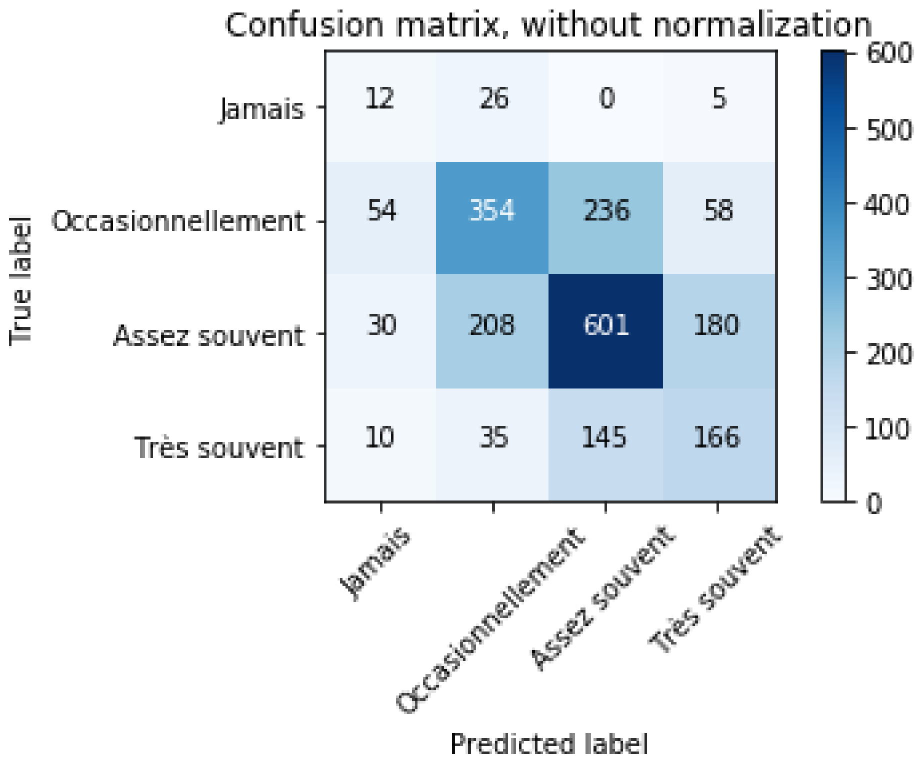
```
In [45]: def plot_confusion_matrix(cm, classes,
                                   normalize=False,
```

```
                              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')
```

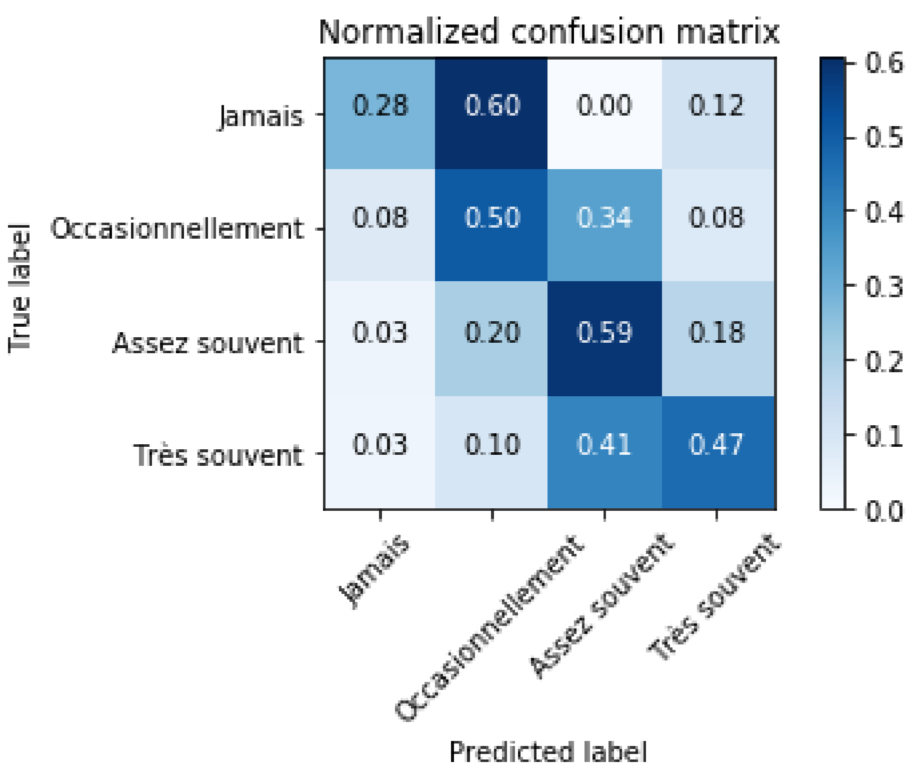
In [46]:
```
# Model evaluation
class_names = ["Jamais",
               "Occasionnellement",
               "Assez souvent",
               "Très souvent" ]
f1_scores = f1_score(y_test, y_test_pred, labels = [1,2,3,4], average=None)
for i,c in enumerate(class_names):
    print(f"f1 score class '{c}' : {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)
```

```python
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')

# 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' : 16.1%
f1 score class 'Occasionnellement' : 53.4%
f1 score class 'Assez souvent' : 60.1%
f1 score class 'Très souvent' : 43.4%
Average scores :
f1 macro : 43.2525 %
f1 weighted : 54.1814 %
acurracy : 53.4434 %
Confusion matrix, without normalization
[[ 12  26   0   5]
 [ 54 354 236  58]
 [ 30 208 601 180]
 [ 10  35 145 166]]
Normalized confusion matrix
[[ 0.28  0.6   0.    0.12]
 [ 0.08  0.5   0.34  0.08]
 [ 0.03  0.2   0.59  0.18]
 [ 0.03  0.1   0.41  0.47]]
```



Confusion matrix, without normalization
True label
Jamais
Occasionnellement
Assez souvent
Très souvent
12 26 0 5
54 354 236 58
30 208 601 180
10 35 145 166
600
500
400
300
200
100
0
Jamais
Occasionnellement
Assez souvent
Très souvent
Predicted label



Normalized confusion matrix
True label
Jamais
Occasionnellement
Assez souvent
Très souvent
0.28 0.60 0.00 0.12
0.08 0.50 0.34 0.08
0.03 0.20 0.59 0.18
0.03 0.10 0.41 0.47
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Jamais
Occasionnellement
Assez souvent
Très souvent
Predicted label