Baseline Model

August 28, 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
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
```

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
```

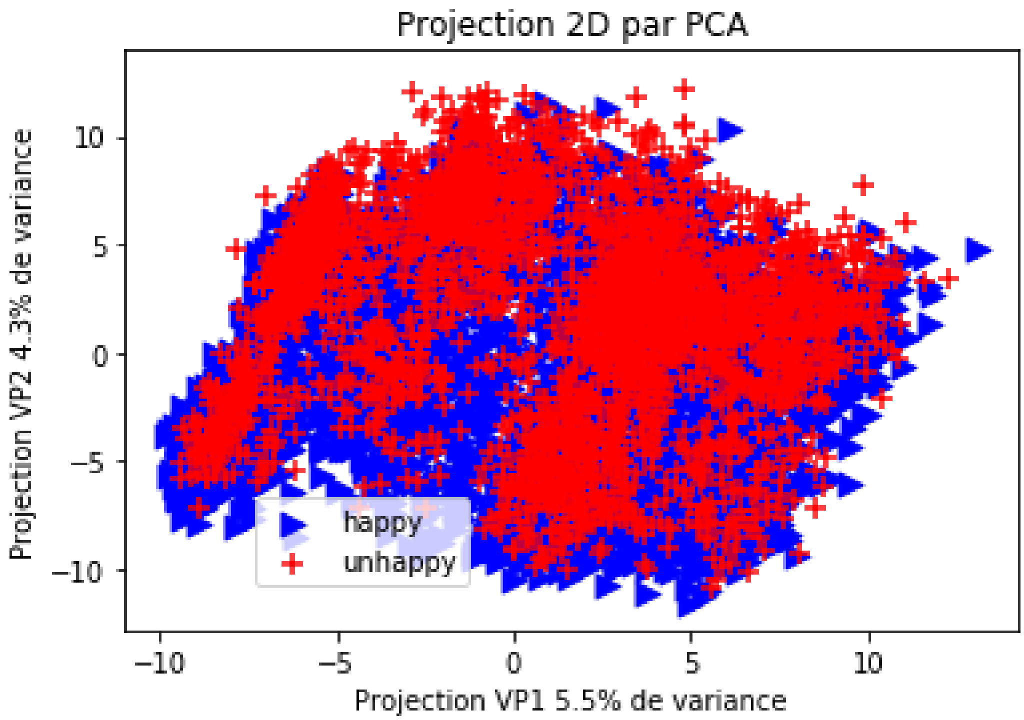
1.2 2) Dataset construction and visualisation

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

```python
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

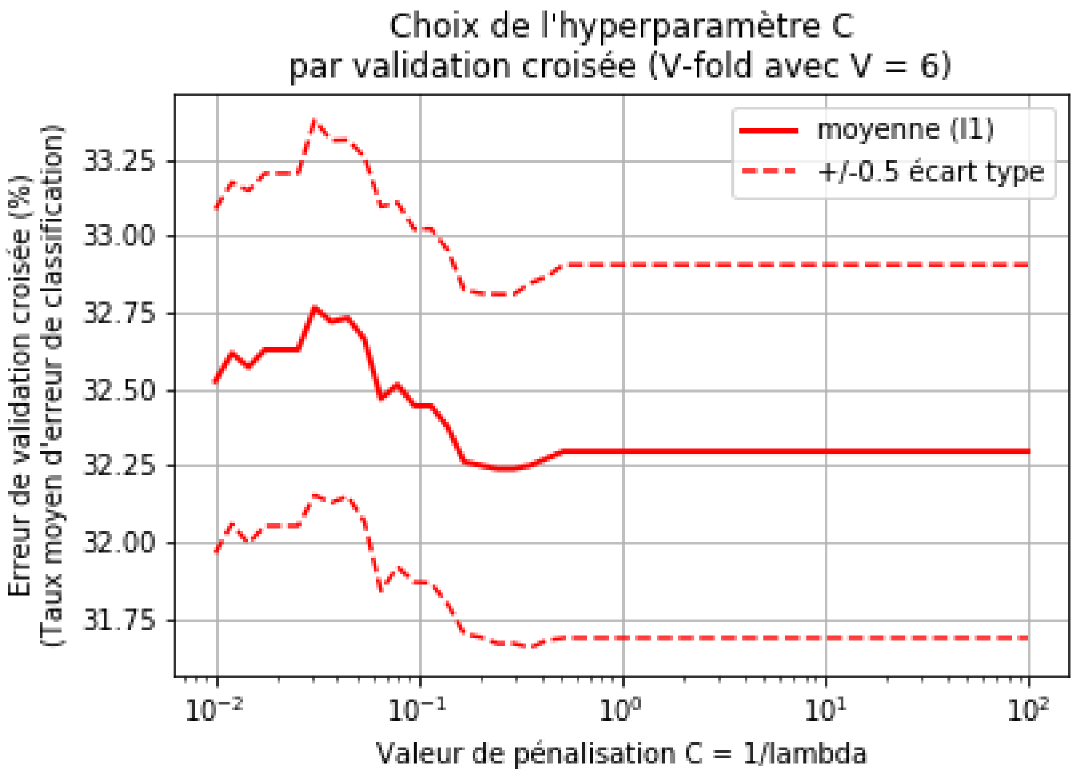
Logistic regression with **4 features** to predict a **2 class** variable

```
In [21]: 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%
```

```
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 23.4 s
Pénalisation l1, valeur optimale : C = 0.24
```

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)
print(f"- F1 score : {f1*100:0.1f} %")
```

```
Model score
- Accuracy : 67.1 %
- F1 score : 74.0 %
```

1.4 4) Feature selection

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

# 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}%")
```

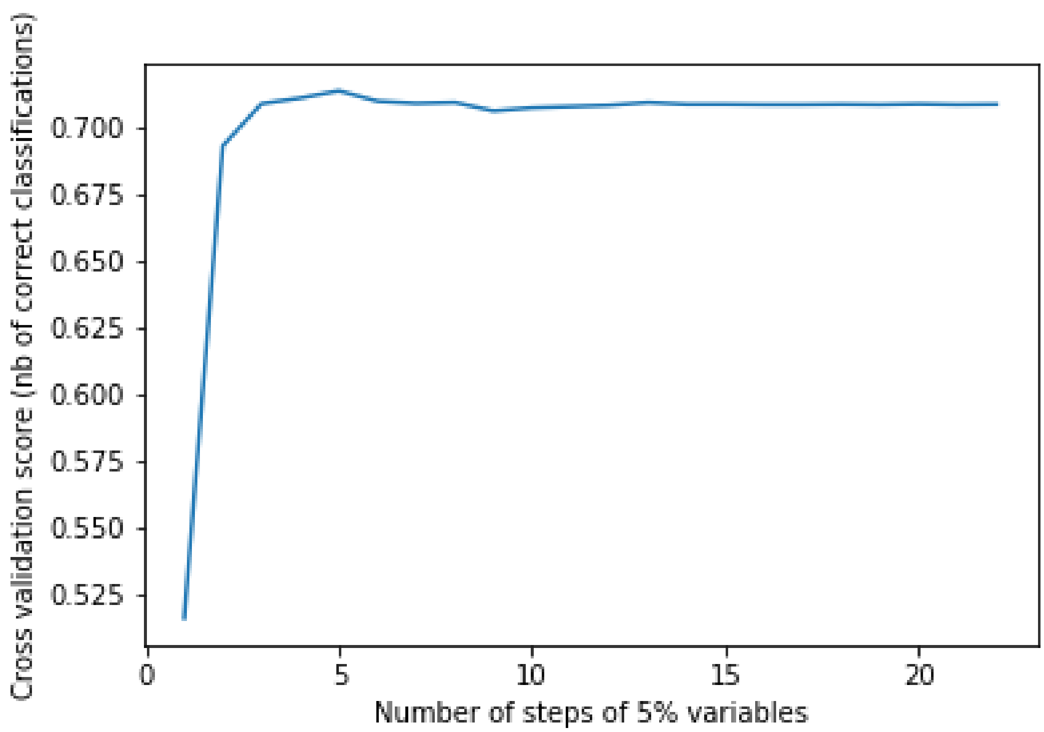
```
11131 exemples before droping na
Number exemple: 10596
- training set: 8476
- test set: 2120
Number of features: p=632
Number of class: 2
class 0 : 34.9%
class 1 : 65.1%
```

1.4.1 a) RFECV using lasso

In [25]:
```
startTime = time.time()
```

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

rfecv = RFECV(estimator=clf, step=0.05, cv=StratifiedKFold(2),
              scoring='accuracy')

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("Number of steps of 5% variables")
plt.ylabel("Cross validation score (nb of correct classifications)")
plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_)
plt.show()
print("Détermination des features optimales en %0.1f s" % (time.time() - startTime))
```

```
Optimal number of features : 105
```




```
Détermination des features optimales en 379.6 s
```

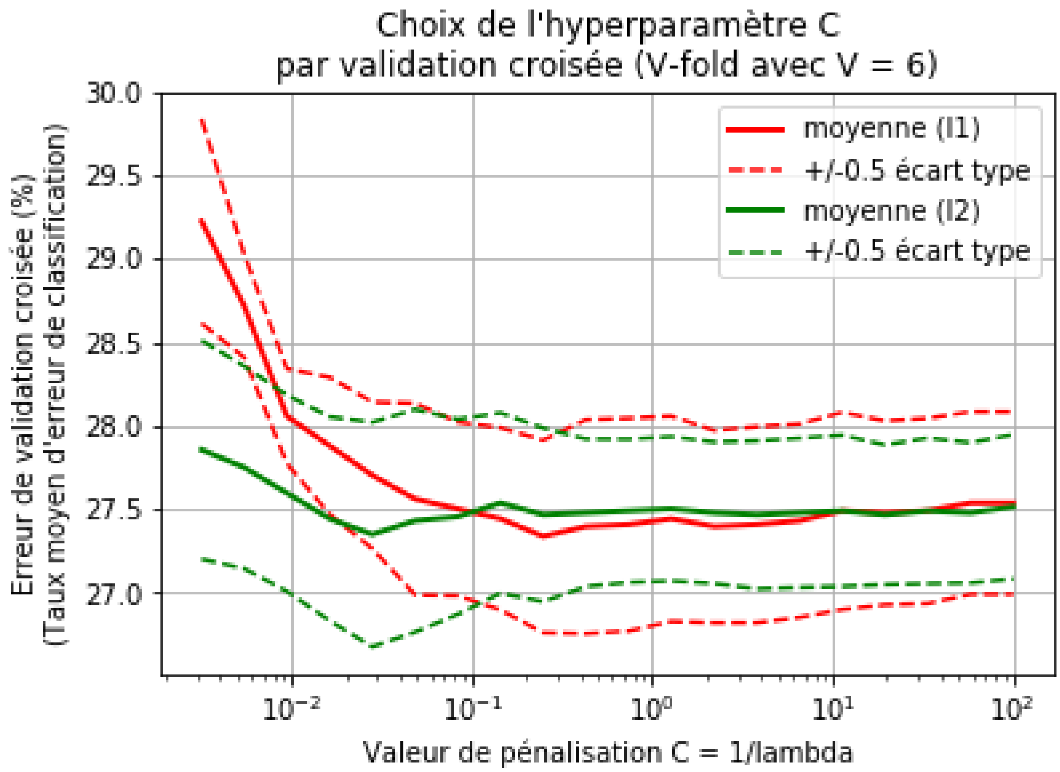
Using slected features to fit various models

```
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
```

```
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 107.5 s
Pénalisation l1, valeur optimale : C = 0.25
Pénalisation l2, valeur optimale : C = 0.03
```

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',
                         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)
print(f"- F1 score : {f1*100:0.1f} %")
```

```
Model score
- Accuracy : 72.1 %
- F1 score : 77.7 %
```

In [29]:
```
# 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',
                         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)
print(f"- F1 score : {f1*100:0.1f} %")
```

```
Model score
- Accuracy : 72.4 %
- F1 score : 78.0 %
```

In [30]:
```
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_
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_} \nAccuracy Score of cross valdation {100

# 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)
accuracy = clf.score(X_test, y_test)
f1 = f1_score(y_test, y_test_pred)
print(f"... done in {time.time() - startTime:0.1f}")
print(f"Random Forest, p={X_train.shape[1]}")
print(f"Model score\n- Accuracy : {accuracy*100:0.1f} %")
print(f"- F1 score : {f1*100:0.1f} %")
```

```
Determination of optimal hyperparameters in 72.4 s
```

```
Optimal values are {'max_depth': 16, 'n_estimators': 64}
Accuracy Score of cross valdation 74.04%
... done in 75.0
Random Forest, p=105
Model score
- Accuracy : 73.1 %
- F1 score : 80.9 %
```

In [31]:
```
touyrt
nb_value = 5 # Number of values tested for hyperparameter

C_log = np.logspace(-5,3,nb_value)
cv = 2 # V-fold, number of folds

params = { 'kernel' :'linear', 'class_weight' : 'balanced'}
clf = SVC(**params)


mean_score_1 = np.empty(nb_value)
std_scores_1 = np.empty(nb_value)

np.random.seed(seed=42)
startTime = time.time()

for i, C in enumerate(C_log):
    params = { 'kernel' :'linear', 'C' : C, 'class_weight' : 'balanced'}
    clf = SVC(**params)
    scores = cross_val_score(clf, X_train, y_train, cv=cv, scoring='accuracy')
    mean_score_1[i] = np.mean(scores)
    std_scores_1[i] = np.std(scores)

# Plotting cross validation score depending on alpha/c value
plt.figure()
plt.semilogx(C_log,mean_score_1[:],'r',linewidth=2,label='SVC average accuracy')
plt.semilogx(C_log,mean_score_1[:]-0.5*std_scores_1[:],'r--',
             label=u'+/-0.5 std dev.')
plt.semilogx(C_log,mean_score_1[:]+0.5*std_scores_1[:],'r--')

plt.xlabel("Regularisation coeficient $C$")
plt.ylabel("Accuracy\n")
plt.title(f"Support Vector Machine - linear kernel\nCross validation (V-fold with V={cv
plt.legend(bbox_to_anchor=(1.5, 1))
plt.grid()
plt.show()
print(f"SVC optimisation in {time.time() - startTime:0.1f}")
print(f"Epsilon fixed at: {0.1:0.4f} \nOptimal value for C: {C_log[np.argmax(mean_score
print(f"Corresponding accuracy : {100*np.max(mean_score_1):0.2f}%")
```

```
# Calculaltion of generalisation score
params = { 'kernel' :'linear', 'C' : C_log[np.argmax(mean_score_1)], 'class_weight' : '
# Learning on full training set with optimals hyperparameters and score on test set
clf = SVC(**params).fit(X_train, y_train)
y_test_pred = clf.predict(X_test)
accuracy = clf.score(X_test, y_test)
f1 = f1_score(y_test, y_test_pred)
print(f"... done in {time.time() - startTime:0.1f}")
print(f"SVM linear p={X_train.shape[1]}")
print(f"Model score\n- Accuracy : {accuracy*100:0.1f} %")
print(f"- F1 score : {f1*100:0.1f} %")
```

```
---------------------------------------------------------------------------

NameError                                 Traceback (most recent call last)

<ipython-input-31-32f1cd8742c0> in <module>()
----> 1 touyrt
      2 nb_value = 5 # Number of values tested for hyperparameter
      3
      4 C_log = np.logspace(-5,3,nb_value)
      5 cv = 2 # V-fold, number of folds


NameError: name 'touyrt' is not defined
```

In [ ]:

```
startTime = time.time()

nb_value = 4
C_log = np.logspace(-2,2,nb_value)
gamma_log = np.logspace(-4,0, nb_value)
param_grid = dict(C=C_log, gamma=gamma_log)

params = { 'kernel' :'rbf', 'class_weight' : 'balanced'}

clf = SVC(**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_} \nAccuracy of cross valdation {100*grid.b

# Learning on full training set with optimals hyperparameters and score on test set
params = {'kernel' :'rbf',
          'C' : grid.best_params_['C'],
          "gamma" : grid.best_params_['gamma'],
```

```
                 'class_weight' : 'balanced'}
        clf = SVC(**params).fit(X_train, y_train)
        y_test_pred = clf.predict(X_test)
        accuracy = clf.score(X_test, y_test)
        f1 = f1_score(y_test, y_test_pred)
        print(f"... done in {time.time() - startTime:0.1f}")
        print(f"SVM with Gaussian kernel, p={X_train.shape[1]}")
        print(f"Model score\n- Accuracy : {accuracy*100:0.1f} %")
        print(f"- F1 score : {f1*100:0.1f} %")
```

1.4.2 a) RFECV using Random Forest

In [47]:
```
pred
```

Out[47]:
```
'HEUREUX_CLF'
```

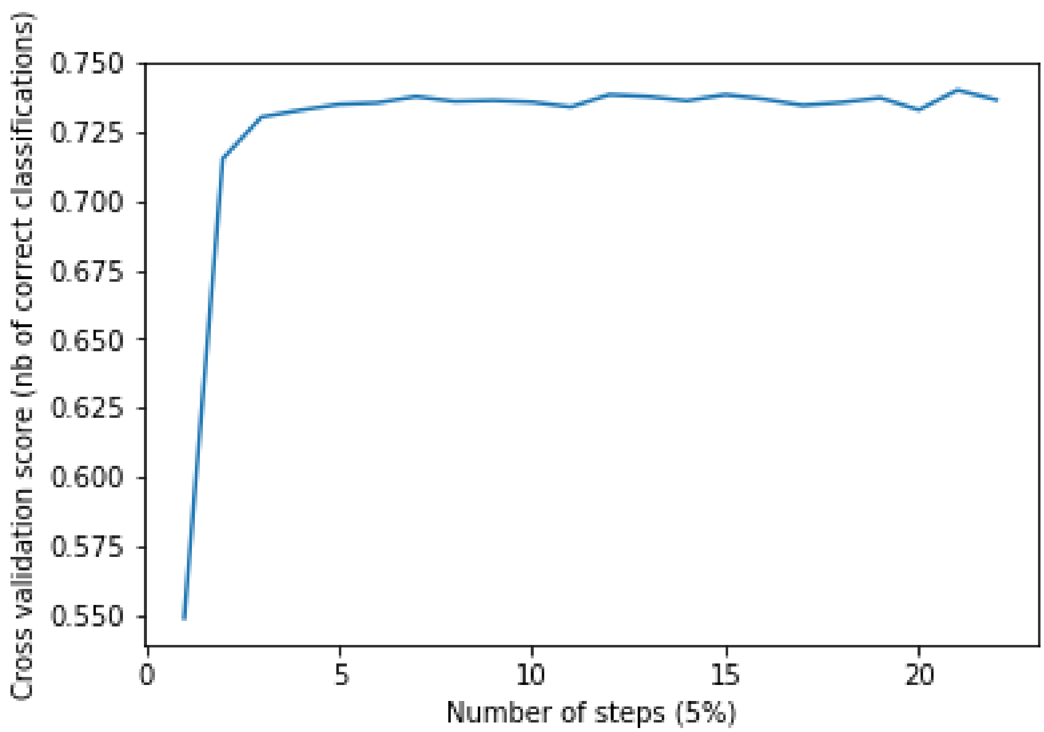
In [50]:
```
features = df.columns.drop(['HEUREUX',"HEUREUX_CLF", "HEUREUX_REG"])
pred = "HEUREUX_CLF"
# treating remaining missing values
print(f"{df.shape[0]} exemples before droping na")
df_tmp = df.loc[:,set(features) | {pred} ].dropna()

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 [36]: startTime = time.time()
         step = 0.05
         params = {'max_features' :'sqrt', 'random_state' : 32,
                   'min_samples_split' : 2, 'class_weight' : 'balanced',
                   'n_estimators' : 256,
                   'max_depth' : 32}
         clf = RandomForestClassifier(**params).fit(X_train, y_train)

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

         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 steps ({step*100:0.0f}%)")
         plt.ylabel("Cross validation score (nb of correct classifications)")
         plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_)
         plt.show()
         print("Détermination des features optimales en %0.1f s" % (time.time() - startTime))
```

```
Optimal number of features : 454
```




```
Détermination des features optimales en 222.2 s
```

```
In [37]: rf_mask = rfecv.support_.copy()
         X_train = X_train[:,rf_mask]
         X_test = X_test[:,rf_mask]
         print(f"Number of features: p={X_train.shape[1]}")
```

```
Number of features: p=454
```

```
In [38]: startTime = time.time()
         n_estimators_range = [16,32,64,128,256]
         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)
    y_test_pred = clf.predict(X_test)
    accuracy = clf.score(X_test, y_test)
    f1 = f1_score(y_test, y_test_pred)
    print(f"... done in {time.time() - startTime:0.1f}")
    print(f"Random Forest, p={X_train.shape[1]}")
    print(f"Model score\n- Accuracy : {accuracy*100:0.1f} %")
    print(f"- F1 score : {f1*100:0.1f} %")
```

```
Determination of optimal hyperparameters in 270.4 s
Optimal values are {'max_depth': 16, 'n_estimators': 256}
Accuracy Score of cross valdation 74.19%
... done in 279.9
Random Forest, p=454
Model score
- Accuracy : 73.5 %
- F1 score : 81.6 %
```

In [39]:
```
np.sum(rf_mask)
```

Out[39]: 454

In [40]:
```
np.sum(lasso_mask)
```

Out[40]: 105

In [51]:
```
len(rf_mask)
```

Out[51]: 477

In [ ]:
```
len(lasso_mask)
```

1.4.3 C) RFECV using SVM (linear kerner)

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

# 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}%")
```

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

        params = {'kernel' :'linear'}
        clf = SVC(**params)

        rfecv = RFECV(estimator=clf, step=0.2, cv=StratifiedKFold(2),
                      scoring='accuracy')


        rfecv.fit(X_train, y_train)
        print("Optimal number of features : %d" % rfecv.n_features_)

        print("Détermination des features optimales en %0.1f s" % (time.time() - startTime))
        # Plot number of features VS. cross-validation scores
        plt.figure()
        plt.xlabel("Number of features selected")
        plt.ylabel("Cross validation score (nb of correct classifications)")
        plt.plot(range(1, len(rfecv.grid_scores_) + 1), rfecv.grid_scores_)
        plt.show()
```

1.4.4 Feature ranking ...

```
In [ ]: # Use regression coefficients to rank features
        clf = LogisticRegression(penalty='l2',C=0.4)

        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(penalty='l1',C=7.2)

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 = len(features)

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

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

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

plt.show()
```

In [ ]:
```
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_w
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_} \nAccuracy Score of cross valdation {100*
```

```
# 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)
y = clf.predict(X_test)
y_test_pred = clf.predict(X_test)
accuracy = clf.score(X_test, y_test)
f1 = f1_score(y_test, y_test_pred)
print(f"... done in {time.time() - startTime:0.1f}")
print(f"Random Forest, p={X_train.shape[1]}")
print(f"Model score\n- Accuracy : {accuracy*100:0.1f} %")
print(f"- F1 score : {f1*100:0.1f} %")
```

1.5 II) Multi class regression

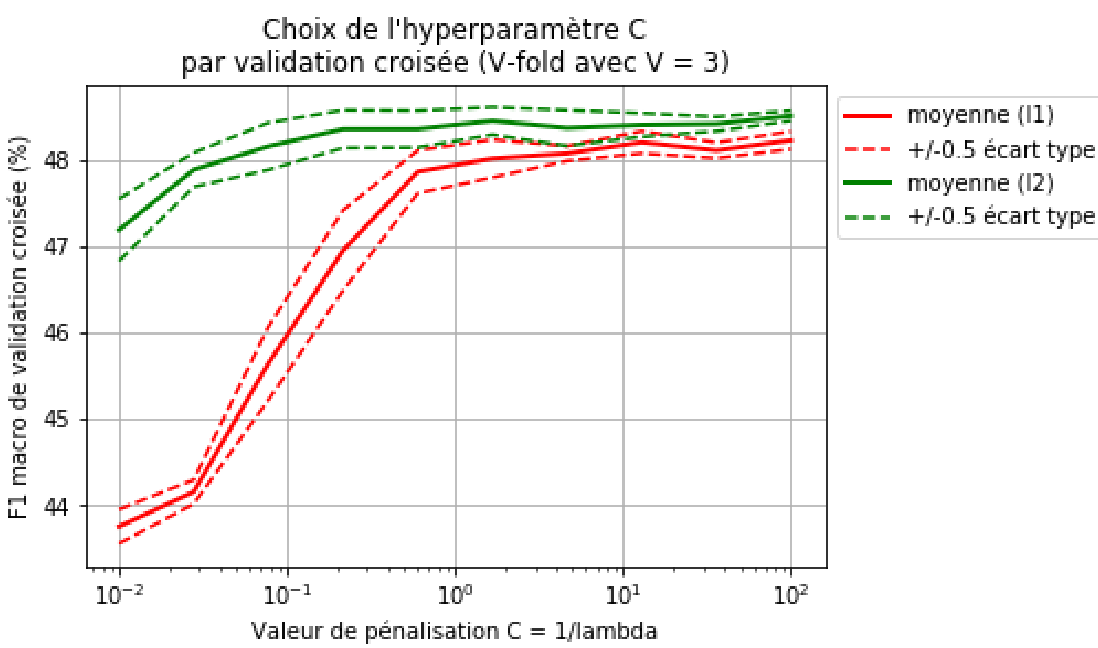
In [56]:
```
features = df.columns.drop(['HEUREUX',"HEUREUX_CLF", "HEUREUX_REG"])
pred = "HEUREUX"

# 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%
```

In [57]:
```python
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_micro'))
    std_scores_l1[i] = 100*np.std(1-cross_val_score(clf,
                                                     X_train,
                                                     y_train,
                                                     cv=cv,
                                                     scoring='f1_micro'))


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_micro'))
    std_scores_l2[i] = 100*np.std(1-cross_val_score(clf,
                                                     X_train,
```

```
                                                    y_train,
                                                    cv=cv,
                                                    scoring='f1_micro'))

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}")
```



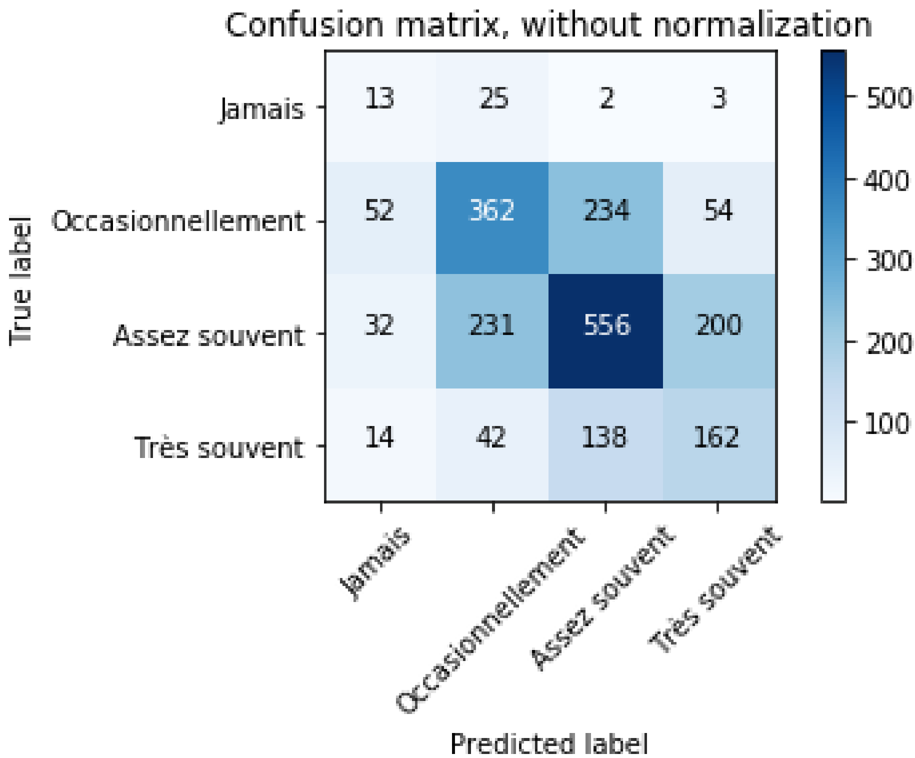
```
Détermination des paramètres optimaux en 5630.4 s
Pénalisation l1, valeur optimale : C = 100.0000
Pénalisation l2, valeur optimale : C = 100.0000
```

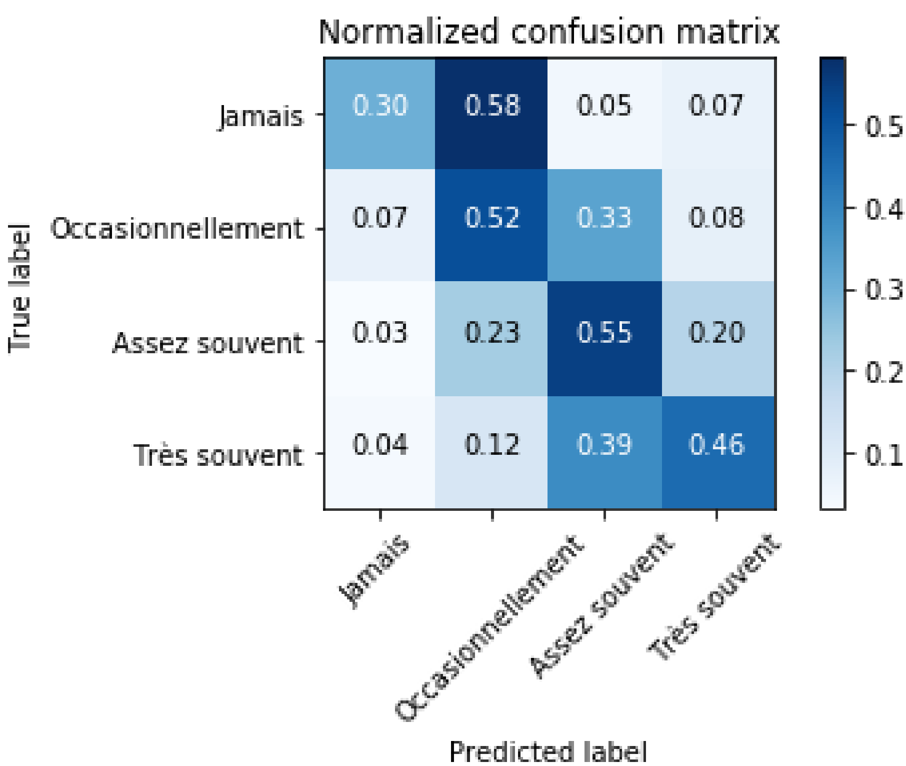
```
In [58]: # Learning on full training set with optimals hyperparameters and score on test set
         clf = LogisticRegression(C=C_log[np.argmax(mean_score_l2)],
                                  penalty='l2',
                                  tol=0.01,
                                  random_state=42,
                                  class_weight='balanced')
         clf.fit(X_train, y_train)
         y_test_pred = clf.predict(X_test)


         # Modelisation as a 5 multi class classification problem

         class_names = ["Jamais",
                        "Occasionnellement",
                        "Assez souvent",
                        "Très souvent" ]
```

```
In [60]: 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')

    # 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')

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

    plt.show()
```

```
Confusion matrix, without normalization
[[ 13  25   2   3]
 [ 52 362 234  54]
 [ 32 231 556 200]
 [ 14  42 138 162]]
Normalized confusion matrix
[[ 0.3   0.58  0.05  0.07]
 [ 0.07  0.52  0.33  0.08]
 [ 0.03  0.23  0.55  0.2 ]
 [ 0.04  0.12  0.39  0.46]]
```


Confusion matrix, without normalization
True label
Jamais
Occasionnellement
Assez souvent
Très souvent
13
25
2
3
52
362
234
54
32
231
556
200
14
42
138
162
500
400
300
200
100
Predicted label


Normalized confusion matrix
True label
Jamais
Occasionnellement
Assez souvent
Très souvent
0.30
0.58
0.05
0.07
0.07
0.52
0.33
0.08
0.03
0.23
0.55
0.20
0.04
0.12
0.39
0.46
0.5
0.4
0.3
0.2
0.1
Predicted label

In [108]:
```
f1_micro = f1_score(y_test, y_test_pred, average='micro')
f1_macro = f1_score(y_test, y_test_pred, average='macro')
f1_weighted = f1_score(y_test, y_test_pred, average='weighted')
acurracy = clf.score(X_test, y_test)
print(f"Score :\nf1 micro : {f1_micro*100:0.4f} %\nf1 macro : {f1_macro*100:0.4f} %\n\
f1 weighted : {f1_weighted*100:0.4f} %\nacurracy : {acurracy*100:0.4f} %")
```

```
Score :
f1 micro : 51.5566 %
f1 macro : 42.2254 %
f1 weighted : 52.3888 %
acurracy : 51.5566 %
```

In [78]:
```
# Recall 'jamais'
13/43
```

Out[78]: 0.3023255813953488

In [79]:
```
# Recall 'Occasionnemmement'
362/(52+362+234+54)
```

Out[79]: 0.5156695156695157

In [80]:
```
# Recall 'assez souvent'
556/(32+231+556+200)
```

Out[80]: 0.5456329735034348

In [67]:
```
len(y_test)
```

Out[67]: 2120

In [68]:
```
13+362+556+162
```

Out[68]: 1093

In [71]:
```
# acurracy
1093/2120
```

Out[71]: 0.5155660377358491

In [83]:
```
# average precision
c1 = 13 +25 + 2+  3
c2 = 52+362+234+ 54
c3 = 32+231+556+200
c4 = 14+ 42+138+162
```

```
In [84]: print(c1,c2,c3,c4)

43 702 1019 356


In [85]: print(len(y_test))

2120


In [91]: c1 = 13 +25 + 2+  3
         c2 = 52+362+234+ 54
         c3 = 32+231+556+200
         c4 = 14+ 42+138+162
         print(c1,c2,c3,c4)
         r1 = 13 / 43
         r2 = 362 / 702
         r3 = 556 / 1019
         r4 = 162 / 366
         print(f"{r1*100:0.2f}% {r2*100:0.2f}% {r3*100:0.2f}% {r4*100:0.2f}%")
         p1 = 13 / (13+52+32+14)
         p2 = 362 / (25 + 362 + 231 + 42)
         p3 = 556 / (2 + 234 + 556 + 138)
         p4 = 162 / (3 + 54 + 200 + 162)
         print(f"{p1*100:0.2f}% {p2*100:0.2f}% {p3*100:0.2f}% {p4*100:0.2f}%")

43 702 1019 356
30.23% 51.57% 54.56% 44.26%
11.71% 54.85% 59.78% 38.66%


In [99]: #average precision
         ap = ((13+52+32+14)*p1 + (25 + 362 + 231 + 42)*p2 +(2 + 234 + 556 + 138)*p3+ (3 + 54 +


         ap = (43*p1 + 702*p2 +1019*p3+ 356*p4)/2120

In [100]: #average recall
          ar = (43*r1 + 702*r2 +1019*r3+ 356*r4)/2120

In [101]: 2 * ap * ar / (ap+ar)

Out[101]: 0.5246335808989457

In [107]: f11 = 2*p1*r1/(p1+r1)
          f12 = 2*p1*r2/(p2+r2)
          f13 = 2*p3*r3/(p3+r3)
          f14 = 2*p4*r4/(p4+r4)
          print(f"{f11:0.4f} {f12:0.4f} {f13:0.4f} {f14:0.4f}")
```

```
0.1688 0.1135 0.5705 0.4127
```

```
In [106]: (f11 + f12 + f13 + f14)/4
```

```
Out[106]: 0.31640614947047796
```

```
In [109]: (f11  + f13 + f14)/3
```

```
Out[109]: 0.38403967394042327
```