

# Felix\_prototype\_V0

October 27, 2018

## 1 Felix prototype

Version 0

Date 21/10/2018

Model used : **Random Forest Classifier** on features selected through **lasso**  
Clustering method used : **Hierarchical clustering** using **ward metric** based on 6 **NOT variable**

```
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
import itertools
import pickle
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_val_score, GridSearchCV
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, f1_score, precision_score, recall_score
from sklearn.model_selection import StratifiedKFold
from sklearn.utils import resample

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

In [3]: # loading data
file = path_data / Path("dataset.csv")
with Path.open(file, 'rb') as fp:
    dataset = pd.read_csv(fp, encoding='utf-8', low_memory=False, index_col = 0)
```

### 1.0.1 Features scope and selection strategy

Features are selected using lasso on the full scope of feature. The 50 more important features (logistic regression coef ranking) are kept regardless of their activability

```

In [4]: # load feature sets
filename = path_dump / Path("dict_features_sets.sav")
with open(filename, 'rb') as fp:
    dict_features_sets = pickle.load(fp)

usual_common_scope_features = dict_features_sets['usual_common_scope_features']

cdv_actionable_individual_1_features = dict_features_sets.get('cdv_actionable_individual_1_features')
cdv_actionable_individual_2_features = dict_features_sets.get('cdv_actionable_individual_2_features')
cdv_actionable_admin_1_features = dict_features_sets.get('cdv_actionable_admin_1_features')
cdv_actionable_admin_2_features = dict_features_sets.get('cdv_actionable_admin_2_features')
insee_recreation_actionable_admin_1_features = dict_features_sets.get('insee_recreation_actionable_admin_1_features')
insee_recreation_actionable_admin_2_features = dict_features_sets.get('insee_recreation_actionable_admin_2_features')
insee_environment_actionable_admin_1_features = dict_features_sets.get('insee_environment_actionable_admin_1_features')
insee_environment_actionable_admin_2_features = dict_features_sets.get('insee_environment_actionable_admin_2_features')
insee_demographics_actionable_admin_1_features = dict_features_sets.get('insee_demographics_actionable_admin_1_features')
insee_demographics_actionable_admin_2_features = dict_features_sets.get('insee_demographics_actionable_admin_2_features')

RFE_LogisticRegression_10_features = dict_features_sets['RFE_LogisticRegression_10_features']
RFE_LogisticRegression_20_features = dict_features_sets['RFE_LogisticRegression_20_features']
RFE_LogisticRegression_50_features = dict_features_sets['RFE_LogisticRegression_50_features']
RFE_LogisticRegression_100_features = dict_features_sets['RFE_LogisticRegression_100_features']

RFE_LinearSVC_100_features = dict_features_sets['RFE_LinearSVC_100_features'],
RFE_LinearSVC_50_features = dict_features_sets['RFE_LinearSVC_50_features'],
RFE_LinearSVC_20_features = dict_features_sets['RFE_LinearSVC_20_features'],
RFE_LinearSVC_10_features = dict_features_sets['RFE_LinearSVC_10_features'],

SelectFromModel_LinearSCV_features = dict_features_sets['SelectFromModel_LinearSCV_features']
SelectFromModel_LogisticRegression_features = dict_features_sets['SelectFromModel_LogisticRegression_features']

In [5]: RFE_LinearSVC_10_features = RFE_LinearSVC_10_features[0]
RFE_LinearSVC_20_features = RFE_LinearSVC_20_features[0]
RFE_LinearSVC_50_features = RFE_LinearSVC_50_features[0]
RFE_LinearSVC_100_features = RFE_LinearSVC_100_features[0]

In [6]: print("The most important features obtained using lasso:")
print(list(SelectFromModel_LogisticRegression_features))

```

The most important features obtained using lasso:

```
['ETATSAN', 'RE_LOG_Oui', 'NOT_PROF', 'INQCHOM3_Non inquiet', 'PCSENQ10_Ouvrier', 'CLASSES0_La c
```

## 1.0.2 Clustering method - feature used

Hierarchical clustering is used using 6 common "NOT\_" variable

```

In [7]: # loading clustering
file = path_data / Path("clustTest3.csv")

```

```
with Path.open(file, 'rb') as fp:
    clustTest1 = pd.read_csv(fp, encoding='utf-8', low_memory=False, sep=";", index_col
```

### 1.0.3 Training set and test set preparation

```
In [8]: df = dataset.loc[:,:]
        # 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

        scope = ( RFE_LinearSVC_20_features ) & set(dataset.columns)
        n_max = 2000

        df = df.loc[:,scope | {"HEUREUX_CLF"} ].dropna()
        features = df.loc[:,scope ].columns

        X = df.loc[:,scope]
        y = df["HEUREUX_CLF"]

        Xs, ys = resample(X, y, random_state=42)

        Xs = Xs.iloc[0:n_max,:]
        ys = ys.iloc[0:n_max]

        X_train, X_test, y_train, y_test = train_test_split(Xs, ys,
                                                            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: 10754
- training set: 1600
- test set: 400
Number of features: p=20
Number of class: 2
```

```
class 0 : 35.1%
class 1 : 64.9%
```

#### 1.0.4 Learning and model performance evaluation on full dataset (before clustering)

```
In [9]: 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 validation {100*grid.best_score_:0.2f}%")

        # Learning on full training set with optimal 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} %")
        res_full = {
            'f1_score' : f1,
            'accuracy' : accuracy,
            'precision' : p,
            'recall' : r
        }
```

```
Determination of optimal hyperparameters in 38.6 s
Optimal values are {'max_depth': 16, 'n_estimators': 128}
```

Accuracy Score of cross validation 74.62%

Random Forest, p=20

Model score

- Accuracy : 74.0 %
- Precision : 76.4 % (Happy # positive class)
- Recall : 84.9 %
- F1 score : 80.5 %

```
In [10]: importances = clf.feature_importances_
std = np.std([tree.feature_importances_ for tree in clf.estimators_],
              axis=0)
indices = np.argsort(importances)[::-1]
features_name = np.array(features)
#features_name_sorted_rf = features_name[indices]
# Print the feature ranking
print("Feature ranking:")

max_features = 15

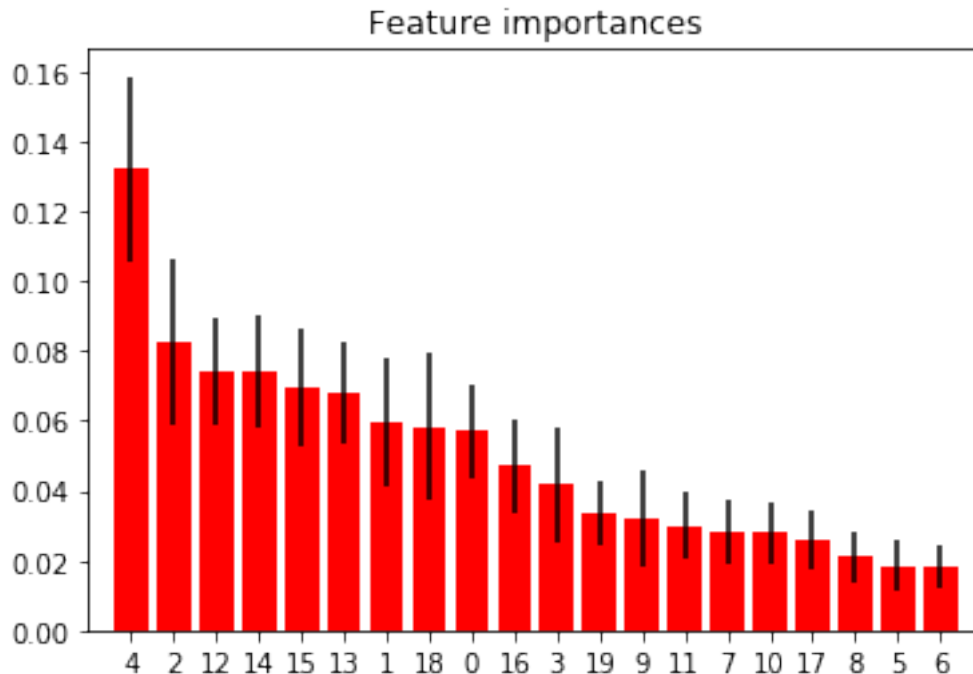
actionable_individual_1_features = cdv_actionable_individual_1_features
actionable_individual_2_features = cdv_actionable_individual_2_features
actionable_admin_1_features = cdv_actionable_admin_1_features | insee_recreation_action
actionable_admin_2_features = cdv_actionable_admin_2_features | insee_recreation_action

for f in range(min(X.shape[1],max_features)):
    print("%d. feature %d -%s- (%f)" % (f + 1, indices[f], features_name[indices[f]], im
    if features_name[indices[f]] in actionable_individual_1_features:
        print("\tActionable at individual level (1)")
    if features_name[indices[f]] in actionable_individual_2_features:
        print("\tActionable at individual level (2)")
    if features_name[indices[f]] in actionable_admin_1_features:
        print("\tActionable at administrative level (1)")
    if features_name[indices[f]] in actionable_admin_2_features:
        print("\tActionable at administrative level (2)")

# Plot the feature importances of the forest
plt.figure()
plt.title("Feature importances")
plt.bar(range(X.shape[1]), importances[indices],
        color="r", yerr=std[indices], align="center")
plt.xticks(range(X.shape[1]), indices)
plt.xlim([-1, X.shape[1]])
plt.show()
```

Feature ranking:

1. feature 4 -AGE- (0.132131)
2. feature 2 -ETATSAN- (0.082846)
  - Actionable at individual level (1)
  - Actionable at administrative level (1)
3. feature 12 -NB\_F121\_NB\_COU- (0.074385)
  - Actionable at administrative level (1)
4. feature 14 -NB\_F111- (0.074378)
  - Actionable at administrative level (1)
5. feature 15 -NIVPERSO- (0.069445)
  - Actionable at individual level (2)
  - Actionable at administrative level (2)
6. feature 13 -NOT\_AMIS- (0.068032)
  - Actionable at individual level (1)
  - Actionable at administrative level (2)
7. feature 1 -CADVIE- (0.059685)
  - Actionable at individual level (1)
  - Actionable at administrative level (1)
8. feature 18 -AGE5- (0.058190)
9. feature 0 -NOT\_FAMI- (0.056968)
  - Actionable at individual level (1)
  - Actionable at administrative level (2)
10. feature 16 -CDV5- (0.047058)
  - Actionable at individual level (2)
  - Actionable at administrative level (1)
11. feature 3 -SOUFFDEP\_Oui- (0.041672)
  - Actionable at individual level (2)
  - Actionable at administrative level (1)
12. feature 19 -NB\_D402- (0.033428)
  - Actionable at administrative level (1)
13. feature 9 -RE\_ALIM\_Oui- (0.032250)
  - Actionable at individual level (2)
  - Actionable at administrative level (2)
14. feature 11 -NB\_D703- (0.029980)
  - Actionable at administrative level (1)
15. feature 7 -CDV5\_4- (0.028340)
  - Actionable at individual level (2)
  - Actionable at administrative level (1)



### 1.0.5 Learning and model performance evaluation on each clusters

```
In [11]: n_estimators_range = [16,32,64,128]
max_depth_range = [2,4,8,16,32,64]
param_grid = dict(n_estimators=n_estimators_range, max_depth = max_depth_range)
params = {'max_features' : 'sqrt',
          'random_state' : 32,
          'min_samples_split' : 2,
          'class_weight' : 'balanced'
        }

scope = ( RFE_LogisticRegression_50_features ) & set(dataset.columns)
features = df.loc[:,scope].columns

In [12]: score_clustering_methods = []
clustering_methods = clustTest1.columns[2:3]

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

```

Xc = X.loc[index_scope.intersection(X.index),:]
yc = y[index_scope.intersection(X.index)]

Xs, ys = resample(Xc, yc, random_state=42)

Xs = Xs.iloc[0:n_max,:]
ys = ys.iloc[0:n_max]

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

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

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

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

y_test_pred = clf.predict(X_test)
accuracy = clf.score(X_test, y_test)
f1 = f1_score(y_test, y_test_pred)

```



```

p = precision_score(y_test, y_test_pred)
r = recall_score(y_test, y_test_pred)

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

cl = {'cluster' : cluster,
      'size' : len(index_scope),
      'model' : 'RandomForestClassifier',
      'params' : params_opt,
      'metrics' : res
      }

score_cluster.append(cl)

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

```

```

-----

Analysis cluster method clust3
liste of clusters : [2 4 6 1 3 5]
cluster 2 : 3053 elements
Number exemple: 2000
    - training set: 1600
    - test set: 400
Number of features: p=20
Number of class: 2
class 0 : 35.1%
class 1 : 64.9%
Optimal values are {'max_depth': 16, 'n_estimators': 128}
cross validation score 79.88%

cluster 4 : 2359 elements
Number exemple: 2000
    - training set: 1600
    - test set: 400
Number of features: p=20
Number of class: 2
class 0 : 35.1%
class 1 : 64.9%
Optimal values are {'max_depth': 16, 'n_estimators': 64}
cross validation score 82.81%

```

cluster 6 : 2313 elements  
 Number exemple: 2000  
     - training set: 1600  
     - test set: 400  
 Number of features: p=20  
 Number of class: 2  
 class 0 : 35.1%  
 class 1 : 64.9%  
 Optimal values are {'max\_depth': 32, 'n\_estimators': 64}  
 cross validation score 83.44%

cluster 1 : 528 elements  
 Number exemple: 510  
     - training set: 408  
     - test set: 102  
 Number of features: p=20  
 Number of class: 2  
 class 0 : 35.1%  
 class 1 : 64.9%  
 Optimal values are {'max\_depth': 16, 'n\_estimators': 128}  
 cross validation score 81.86%

cluster 3 : 1384 elements  
 Number exemple: 1361  
     - training set: 1088  
     - test set: 273  
 Number of features: p=20  
 Number of class: 2  
 class 0 : 35.1%  
 class 1 : 64.9%  
 Optimal values are {'max\_depth': 32, 'n\_estimators': 64}  
 cross validation score 84.74%

cluster 5 : 1494 elements  
 Number exemple: 1466  
     - training set: 1172  
     - test set: 294  
 Number of features: p=20  
 Number of class: 2  
 class 0 : 35.1%  
 class 1 : 64.9%  
 Optimal values are {'max\_depth': 32, 'n\_estimators': 128}  
 cross validation score 82.76%

## 1.0.6 Performance gain obtained using clustering

In [13]: # F1 score

```
for score_method in score_clustering_methods:
    print(f"method {score_method['clustering_method']}:")
    average_score = 0
    total_size = 0
    for i, score_cluster in enumerate(score_method['cluster_scores']):
        print(f"cluster {score_cluster['cluster']} ({score_cluster['size']}), f1 macro {score_cluster['metrics']['f1_score']}")
        average_score += score_cluster['metrics']['f1_score']*score_cluster['size']
        total_size += score_cluster['size']

    average_score = average_score / total_size
    print(f"average f1 on clusters {100*average_score:0.1f}% gain {100*(average_score-r
```

```
method clust3:
cluster 2 (3053), f1 macro 84.2%
cluster 4 (2359), f1 macro 90.9%
cluster 6 (2313), f1 macro 91.6%
cluster 1 (528), f1 macro 89.8%
cluster 3 (1384), f1 macro 94.6%
cluster 5 (1494), f1 macro 88.3%
average f1 on clusters 89.3% gain 8.8
```

In [14]: # accuracy

```
for score_method in score_clustering_methods:
    print(f"method {score_method['clustering_method']}:")
    average_score = 0
    total_size = 0
    for i, score_cluster in enumerate(score_method['cluster_scores']):
        print(f"cluster {score_cluster['cluster']} ({score_cluster['size']}) , accuracy {score_cluster['metrics']['accuracy']}")
        average_score = average_score + score_cluster['metrics']['accuracy']*score_cluster['size']
        total_size += score_cluster['size']
    average_score = average_score / total_size
    print(f"average accuracy on clusters {100*average_score:0.1f}% gain {100*(average_s
```

```
method clust3:
cluster 2 (3053) , accuracy 79.5%
cluster 4 (2359) , accuracy 87.0%
cluster 6 (2313) , accuracy 88.0%
cluster 1 (528) , accuracy 87.3%
cluster 3 (1384) , accuracy 92.3%
cluster 5 (1494) , accuracy 86.4%
average accuracy on clusters 85.7% gain 11.7
```

### **1.0.7 Feature importance of the models & actionable variables**