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
cdv_actionable_individual_2_features = dict_features_sets.get('cdv_actionable_individual
cdv_actionable_admin_1_features = dict_features_sets.get('cdv_actionable_admin_1_feature
cdv_actionable_admin_2_features = dict_features_sets.get('cdv_actionable_admin_2_feature
insee_recreation_actionable_admin_1_features = dict_features_sets.get('insee_recreation_
insee_recreation_actionable_admin_2_features = dict_features_sets.get('insee_recreation_
insee_environment_actionable_admin_1_features = dict_features_sets.get('insee_environmen
insee_environment_actionable_admin_2_features = dict_features_sets.get('insee_environmen
insee_demographics_actionable_admin_1_features = dict_features_sets.get('insee_demograph
insee_demographics_actionable_admin_2_features = dict_features_sets.get('insee_demograph

RFE_LogisticRegression_10_features = dict_features_sets['RFE_LogisticRegression_10_featu
RFE_LogisticRegression_20_features = dict_features_sets['RFE_LogisticRegression_20_featu
RFE_LogisticRegression_50_features = dict_features_sets['RFE_LogisticRegression_50_featu
RFE_LogisticRegression_100_features = dict_features_sets['RFE_LogisticRegression_100_fea
```

In [5]:
```
insee_environment_actionable_admin_1_features
```

Out[5]:
```
set()
```

In [6]:
```
print("The 50 most important features obtained using lasso:")
print(list(RFE_LogisticRegression_50_features))
```

```
The 50 most important features obtained using lasso:
['SITUEMP3_Inactif', 'HANDICAP_Oui', 'CADVIE', 'BANQEPA_Oui', 'RESTRICT_Oui', 'TRAVFEM_Elles dev
```

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_LogisticRegression_50_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: 10788
- training set: 1600
- test set: 400
Number of features: p=50
Number of class: 2
class 0 : 35.0%
class 1 : 65.0%
```

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]
```

```python
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} %")
res_full  = {
    'f1_score' : f1,
    'accuracy' : accuracy,
    'precision' : p,
    'recall' : r
}
```

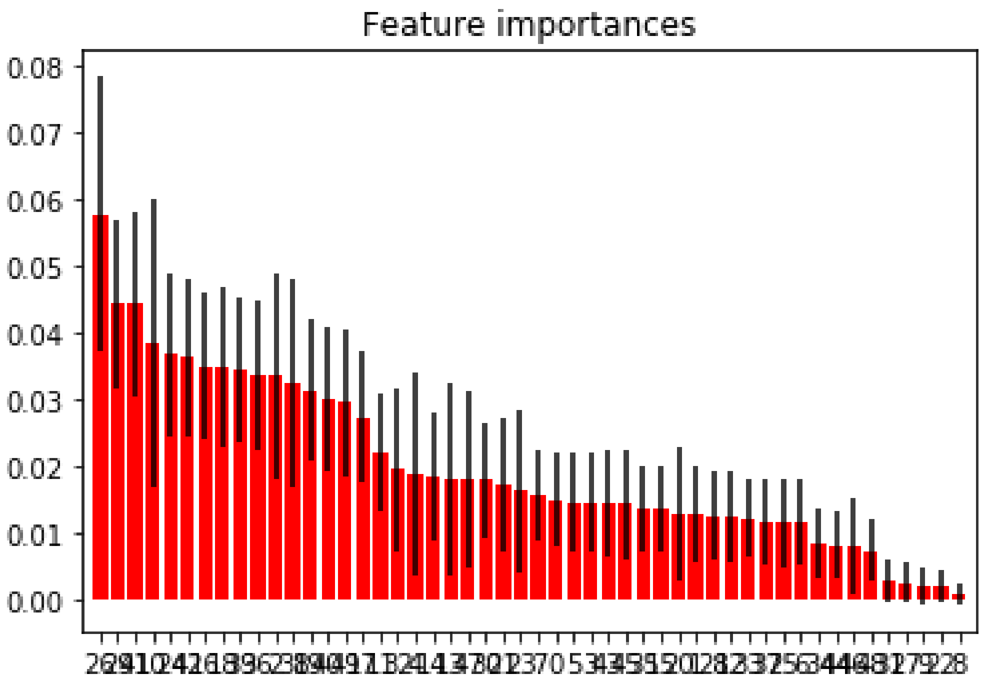
```
Determination of optimal hyperparameters in 52.6 s
Optimal values are {'max_depth': 16, 'n_estimators': 512}
Accuracy Score of cross valdation 76.25%
Random Forest, p=50
Model score
- Accuracy : 73.8 %
- Precision : 73.7 % (Happy # positive class)
- Recall : 90.9 %
- F1 score : 81.4 %
```

In [10]:
```python
importances = clf.feature_importances_
```

```python
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 26 -revtot7- (0.057745)
        Actionable at individual level (2)
        Actionable at administrative level (2)
2. feature 29 -NOT_PROF- (0.044283)
        Actionable at individual level (1)
        Actionable at administrative level (2)
3. feature 41 -NOT_AMIS- (0.044214)
        Actionable at individual level (1)
```

```
        Actionable at administrative level (2)
4. feature 10 -SOUFFDEP_Oui- (0.038417)
        Actionable at individual level (2)
        Actionable at administrative level (1)
5. feature 24 -NIVPERSO- (0.036614)
        Actionable at individual level (2)
        Actionable at administrative level (2)
6. feature 42 -NOT_LIBR- (0.036320)
        Actionable at individual level (1)
        Actionable at administrative level (1)
7. feature 16 -NBENF6- (0.034997)
        Actionable at individual level (2)
        Actionable at administrative level (2)
8. feature 18 -NOT_FAMI- (0.034783)
        Actionable at individual level (1)
        Actionable at administrative level (2)
9. feature 39 -CDV5- (0.034334)
        Actionable at individual level (2)
        Actionable at administrative level (1)
10. feature 36 -INQALIM- (0.033529)
        Actionable at individual level (1)
        Actionable at administrative level (1)
11. feature 2 -CADVIE- (0.033426)
        Actionable at individual level (1)
        Actionable at administrative level (1)
12. feature 38 -ETATSAN- (0.032443)
        Actionable at individual level (1)
        Actionable at administrative level (1)
13. feature 19 -INQCHOMA- (0.031362)
        Actionable at individual level (1)
        Actionable at administrative level (1)
14. feature 40 -CONFENTR- (0.030018)
        Actionable at individual level (1)
        Actionable at administrative level (1)
15. feature 49 -SECURITE- (0.029530)
        Actionable at individual level (2)
        Actionable at administrative level (1)
```



1.0.5 Learning and model performance evaluation on each clusters

In [11]:
```python
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]:
```python
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=50
Number of class: 2
class 0 : 35.0%
class 1 : 65.0%
Optimal values are {'max_depth': 32, 'n_estimators': 128}
cross validation score 80.75%

cluster 4 : 2359 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=50
Number of class: 2
class 0 : 35.0%
class 1 : 65.0%
Optimal values are {'max_depth': 16, 'n_estimators': 32}
cross validation score 84.12%
```

```
cluster 6 : 2313 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=50
Number of class: 2
class 0 : 35.0%
class 1 : 65.0%
Optimal values are {'max_depth': 16, 'n_estimators': 64}
cross validation score 83.50%

cluster 1 : 528 elements
Number exemple: 505
        - training set: 404
        - test set: 101
Number of features: p=50
Number of class: 2
class 0 : 35.0%
class 1 : 65.0%
Optimal values are {'max_depth': 16, 'n_estimators': 32}
cross validation score 82.67%

cluster 3 : 1384 elements
Number exemple: 1367
        - training set: 1093
        - test set: 274
Number of features: p=50
Number of class: 2
class 0 : 35.0%
class 1 : 65.0%
Optimal values are {'max_depth': 16, 'n_estimators': 128}
cross validation score 86.18%

cluster 5 : 1494 elements
Number exemple: 1472
        - training set: 1177
        - test set: 295
Number of features: p=50
Number of class: 2
class 0 : 35.0%
class 1 : 65.0%
Optimal values are {'max_depth': 16, 'n_estimators': 128}
cross validation score 83.60%
```

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
        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 90.2%
cluster 4 (2359), f1 macro 91.7%
cluster 6 (2313), f1 macro 92.6%
cluster 1 (528), f1 macro 87.2%
cluster 3 (1384), f1 macro 92.1%
cluster 5 (1494), f1 macro 88.9%
average f1 on clusters 90.9% gain 9.5
```

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
        average_score = average_score + score_cluster['metrics']['accuracy']*score_clus
        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 86.0%
cluster 4 (2359) , accuracy 87.8%
cluster 6 (2313) , accuracy 89.0%
cluster 1 (528) , accuracy 88.1%
cluster 3 (1384) , accuracy 88.3%
cluster 5 (1494) , accuracy 86.8%
average accuracy on clusters 87.5% gain 13.7
```

1.0.7 Feature importance of the models & actionable variables