Felix_prototype_V0

October 21, 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_features = dict_features_sets['usual_common_features']
        cdv_actionable_individual_1_features = dict_features_sets['cdv_actionable_individual_1_f
        cdv_actionable_individual_2_features = dict_features_sets['cdv_actionable_individual_2_f
        RFE_LogisticRegression_50_features = dict_features_sets['RFE_LogisticRegression_50_featu
```

```
In [5]: print("The 50 most important features obtained using lasso:")
        print(list(RFE_LogisticRegression_50_features))
```

```
The 50 most important features obtained using lasso:
['CONFENTR', 'TRAVFEM_Elles devraient travailler quand elles le désirent', 'SOUFFNER_Oui', 'PROG
```

1.0.2 Clustering method - feature used

Hierarchical clustering is used using 6 common "NOT_" variable

```
In [6]: # 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 [7]: 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]
```

```python
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 [8]:
```python
startTime = time.time()
n_estimators_range = [32,64,128,256,512]
max_depth_range = [4,8,16,32,64]
param_grid = dict(n_estimators=n_estimators_range, max_depth = max_depth_range)

params = {'max_features' :'sqrt', 'random_state' : 32,
          'min_samples_split' : 2, 'class_weight' : 'balanced'}
clf = RandomForestClassifier(**params)

grid = GridSearchCV(clf, scoring='accuracy', param_grid=param_grid)
grid.fit(X_train, y_train)
print(f"Determination of optimal hyperparameters in {time.time() - startTime:0.1f} s")
print(f"Optimal values are {grid.best_params_} \n\
Accuracy Score of cross valdation {100*grid.best_score_:0.2f}%")

# Learning on full training set with optimals hyperparameters and score on test set
params = {'max_features' :'sqrt', 'random_state' : 32,
          'min_samples_split' : 2, 'class_weight' : 'balanced',
          'n_estimators' : grid.best_params_['n_estimators'],
          'max_depth' : grid.best_params_['max_depth']}
```

```
        clf = RandomForestClassifier(**params).fit(X_train, y_train)
        clf.fit(X_train, y_train)
        y_test_pred = clf.predict(X_test)

        print(f"Random Forest, p={X_train.shape[1]}")
        accuracy = clf.score(X_test, y_test)
        f1 = f1_score(y_test, y_test_pred)
        p = precision_score(y_test, y_test_pred)
        r = recall_score(y_test, y_test_pred)
        print(f"Model score\n- Accuracy : {accuracy*100:0.1f} %")
        print(f"- Precision : {p*100:0.1f} % (Happy # positive class)")
        print(f"- Recall : {r*100:0.1f} %")
        print(f"- F1 score : {f1*100:0.1f} %")
        res_full  = {
            'f1_score' : f1,
            'accuracy' : accuracy,
            'precision' : p,
            'recall' : r
        }
```

```
Determination of optimal hyperparameters in 48.0 s
Optimal values are {'max_depth': 32, 'n_estimators': 256}
Accuracy Score of cross valdation 76.12%
Random Forest, p=50
Model score
- Accuracy : 73.2 %
- Precision : 73.7 % (Happy # positive class)
- Recall : 89.7 %
- F1 score : 80.9 %
```

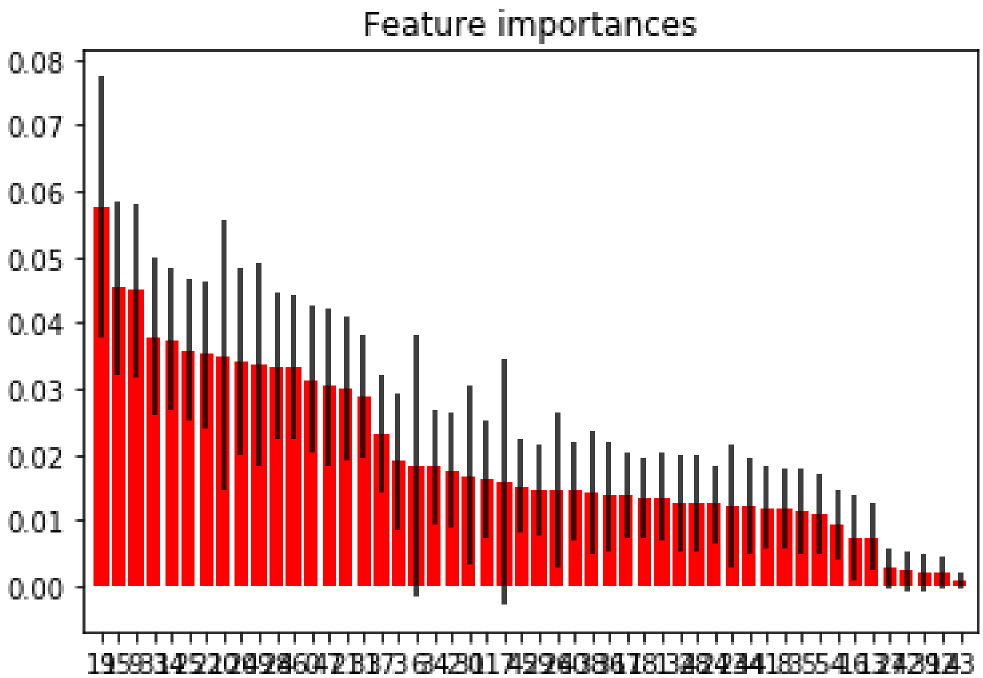
```
In [9]: importances = clf.feature_importances_
        std = np.std([tree.feature_importances_ for tree in clf.estimators_],
                     axis=0)
        indices = np.argsort(importances)[::-1]
        features_name = np.array(features)
        #features_name_sorted_rf = features_name[indices]
        # Print the feature ranking
        print("Feature ranking:")

        max_features = 15

        for f in range(min(X.shape[1],max_features)):
            print("%d. feature %d -%s- (%f)" % (f + 1, indices[f],features_name[indices[f]], imp
            if features_name[indices[f]] in cdv_actionable_individual_1_features:
                print("\tActionable at individual level (1)")
            elif features_name[indices[f]] in cdv_actionable_individual_2_features:
                print("\tActionable at individual level (2)")
```

```python
# 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 19 -revtot7- (0.057628)
        Actionable at individual level (2)
2. feature 15 -NOT_PROF- (0.045291)
        Actionable at individual level (1)
3. feature 9 -NOT_AMIS- (0.044856)
        Actionable at individual level (1)
4. feature 33 -NIVPERSO- (0.037919)
        Actionable at individual level (2)
5. feature 14 -NOT_LIBR- (0.037460)
        Actionable at individual level (1)
6. feature 25 -CDV5- (0.035741)
        Actionable at individual level (2)
7. feature 22 -NBENF6- (0.035219)
        Actionable at individual level (2)
8. feature 10 -SOUFFDEP_Oui- (0.035098)
        Actionable at individual level (2)
9. feature 20 -CADVIE- (0.034076)
        Actionable at individual level (1)
10. feature 49 -ETATSAN- (0.033789)
        Actionable at individual level (1)
11. feature 28 -INQALIM- (0.033493)
        Actionable at individual level (1)
12. feature 46 -NOT_FAMI- (0.033475)
        Actionable at individual level (1)
13. feature 0 -CONFENTR- (0.031363)
        Actionable at individual level (1)
14. feature 47 -SECURITE- (0.030271)
        Actionable at individual level (2)
15. feature 21 -INQCHOMA- (0.030152)
        Actionable at individual level (1)
```



1.0.5 Learning and model performance evaluation on each clusters

```
In [10]: 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 [11]: 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")
```

```python
        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': 16, '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': 128}
cross validation score 84.06%
```

```
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': 32, 'n_estimators': 32}
cross validation score 82.75%

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': 64}
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': 32}
cross validation score 83.86%
```

1.0.6 Performance gain obtained using clustering

In [12]:
```
# 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 88.8%
cluster 4 (2359), f1 macro 92.9%
cluster 6 (2313), f1 macro 93.0%
cluster 1 (528), f1 macro 89.1%
cluster 3 (1384), f1 macro 92.3%
cluster 5 (1494), f1 macro 87.7%
average f1 on clusters 90.8% gain 9.9
```

In [13]:
```
# 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 84.2%
cluster 4 (2359) , accuracy 89.5%
cluster 6 (2313) , accuracy 89.8%
cluster 1 (528) , accuracy 90.1%
cluster 3 (1384) , accuracy 88.7%
cluster 5 (1494) , accuracy 85.4%
average accuracy on clusters 87.5% gain 14.2
```

1.0.7 Feature importance of the models & actionable variables