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

        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_featu
        SelectFromModel_LogisticRegression_features = dict_features_sets['SelectFromModel_Logist
```

```
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]
        SelectFromModel_LinearSCV_features = SelectFromModel_LinearSCV_features[0]
```

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

```
The most important features obtained using lasso:
['SITUEMP3_Inactif', 'SITUFAM_Couple sans enfants', 'RE_VOIT_Oui', 'PROGRAD_nan', 'TRAVFEM_Elles
```

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_100_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: 10630
- training set: 1600
- test set: 400
Number of features: p=100
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)

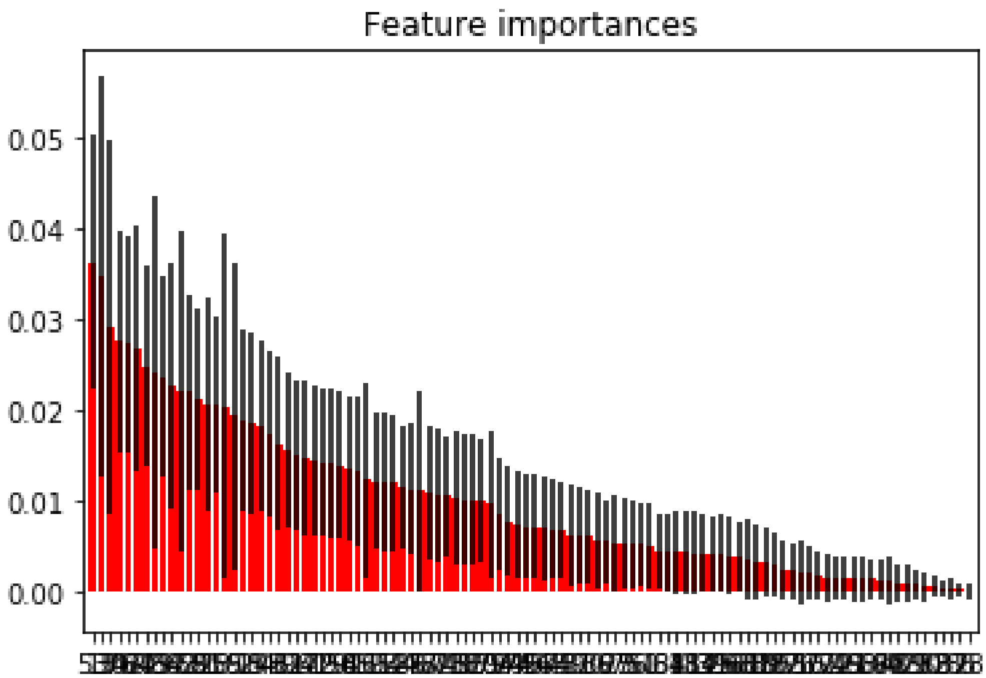
```
In [9]: startTime = time.time()
        n_estimators_range = [32,64,128,256,512]
        max_depth_range = [4,8,16,32,64]
        param_grid = dict(n_estimators=n_estimators_range, max_depth = max_depth_range)

        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 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 55.2 s
Optimal values are {'max_depth': 16, 'n_estimators': 512}
```

```
Accuracy Score of cross valdation 74.88%
Random Forest, p=100
Model score
- Accuracy : 73.0 %
- Precision : 71.6 % (Happy # positive class)
- Recall : 94.0 %
- F1 score : 81.3 %
```

```
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 53 -AGE- (0.036196)
2. feature 13 -ETATSAN- (0.034628)
        Actionable at individual level (1)
        Actionable at administrative level (1)
3. feature 30 -NIVPERSO- (0.029086)
        Actionable at individual level (2)
        Actionable at administrative level (2)
4. feature 76 -P15_RSECOCC- (0.027562)
        Actionable at administrative level (1)
5. feature 47 -ETAZ15- (0.027234)
        Actionable at administrative level (1)
6. feature 64 -NOT_AMIS- (0.026779)
        Actionable at individual level (1)
        Actionable at administrative level (2)
7. feature 92 -DECESD16- (0.024812)
        Actionable at administrative level (1)
8. feature 73 -RE_VOIT_Oui- (0.024049)
        Actionable at individual level (2)
        Actionable at administrative level (2)
9. feature 66 -NB_A403- (0.023601)
        Actionable at administrative level (1)
10. feature 97 -CADVIE- (0.022627)
        Actionable at individual level (1)
        Actionable at administrative level (1)
11. feature 42 -SOUFFDEP_Oui- (0.022102)
        Actionable at individual level (2)
        Actionable at administrative level (1)
12. feature 58 -NOT_LIBR- (0.021931)
        Actionable at individual level (1)
        Actionable at administrative level (1)
13. feature 32 -NOT_PROF- (0.021154)
        Actionable at individual level (1)
        Actionable at administrative level (2)
14. feature 91 -NOT_FAMI- (0.020646)
        Actionable at individual level (1)
        Actionable at administrative level (2)
15. feature 18 -NB_A501- (0.020537)
        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=100
Number of class: 2
class 0 : 35.1%
class 1 : 64.9%
Optimal values are {'max_depth': 16, 'n_estimators': 32}
cross validation score 80.00%

cluster 4 : 2359 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=100
Number of class: 2
class 0 : 35.1%
class 1 : 64.9%
Optimal values are {'max_depth': 16, 'n_estimators': 128}
cross validation score 83.62%
```

```
cluster 6 : 2313 elements
Number exemple: 2000
        - training set: 1600
        - test set: 400
Number of features: p=100
Number of class: 2
class 0 : 35.1%
class 1 : 64.9%
Optimal values are {'max_depth': 32, 'n_estimators': 32}
cross validation score 84.69%

cluster 1 : 528 elements
Number exemple: 495
        - training set: 396
        - test set: 99
Number of features: p=100
Number of class: 2
class 0 : 35.1%
class 1 : 64.9%
Optimal values are {'max_depth': 8, 'n_estimators': 32}
cross validation score 79.04%

cluster 3 : 1384 elements
Number exemple: 1354
        - training set: 1083
        - test set: 271
Number of features: p=100
Number of class: 2
class 0 : 35.1%
class 1 : 64.9%
Optimal values are {'max_depth': 32, 'n_estimators': 128}
cross validation score 85.50%

cluster 5 : 1494 elements
Number exemple: 1449
        - training set: 1159
        - test set: 290
Number of features: p=100
Number of class: 2
class 0 : 35.1%
class 1 : 64.9%
Optimal values are {'max_depth': 8, 'n_estimators': 128}
cross validation score 80.67%
```

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 85.6%
cluster 4 (2359), f1 macro 87.9%
cluster 6 (2313), f1 macro 90.8%
cluster 1 (528), f1 macro 87.6%
cluster 3 (1384), f1 macro 93.5%
cluster 5 (1494), f1 macro 87.7%
average f1 on clusters 88.5% gain 7.3
```

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 82.0%
cluster 4 (2359) , accuracy 83.8%
cluster 6 (2313) , accuracy 86.2%
cluster 1 (528) , accuracy 84.8%
cluster 3 (1384) , accuracy 90.8%
cluster 5 (1494) , accuracy 85.5%
average accuracy on clusters 85.0% gain 12.0
```

1.0.7 Feature importance of the models & actionable variables