PCA_SVM_python

January 22, 2021

1 Projet TP Groupe 3

1.1 Nous avons utilisé les étapes suivantes :

1.2 1. Réduction de la dimension des variables avec PCA

1.3 2. Utilisation de SVM pour la classification

[1]:
```
# On impoete les librairies

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.decomposition import PCA
from sklearn import preprocessing
from sklearn.pipeline import make_pipeline, Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import GridSearchCV, learning_curve
```

1.3.1 On importe les données d'apprentissage

[2]:
```
path_dataset = "UCI HAR Dataset/"
```

[3]:
```
dataset_train = pd.read_csv(path_dataset + "train/X_train_new.txt", sep=' ',␣
↪header=None)
dataset_train
```

[3]:
```
          0         1         2         3         4         5         6    \
0  0.288585 -0.020294 -0.132905 -0.995279 -0.983111 -0.913526 -0.995112
1  0.278419 -0.016411 -0.123520 -0.998245 -0.975300 -0.960322 -0.998807
2  0.279653 -0.019467 -0.113462 -0.995380 -0.967187 -0.978944 -0.996520
```

```
3     0.279174 -0.026201 -0.123283 -0.996091 -0.983403 -0.990675 -0.997099
4     0.276629 -0.016570 -0.115362 -0.998139 -0.980817 -0.990482 -0.998321
…          …         …         …         …         …         …         …
7347  0.299665 -0.057193 -0.181233 -0.195387  0.039905  0.077078 -0.282301
7348  0.273853 -0.007749 -0.147468 -0.235309  0.004816  0.059280 -0.322552
7349  0.273387 -0.017011 -0.045022 -0.218218 -0.103822  0.274533 -0.304515
7350  0.289654 -0.018843 -0.158281 -0.219139 -0.111412  0.268893 -0.310487
7351  0.351503 -0.012423 -0.203867 -0.269270 -0.087212  0.177404 -0.377404

             7         8         9   …       553       554       555  \
0    -0.983185 -0.923527 -0.934724  … -0.710304 -0.112754  0.030400
1    -0.974914 -0.957686 -0.943068  … -0.861499  0.053477 -0.007435
2    -0.963668 -0.977469 -0.938692  … -0.760104 -0.118559  0.177899
3    -0.982750 -0.989302 -0.938692  … -0.482845 -0.036788 -0.012892
4    -0.979672 -0.990441 -0.942469  … -0.699205  0.123320  0.122542
…          …         …         …  …  …         …         …
7347  0.043616  0.060410  0.210795  … -0.880324 -0.190437  0.829718
7348 -0.029456  0.080585  0.117440  … -0.680744  0.064907  0.875679
7349 -0.098913  0.332584  0.043999  … -0.304029  0.052806 -0.266724
7350 -0.068200  0.319473  0.101702  … -0.344314 -0.101360  0.700740
7351 -0.038678  0.229430  0.269013  … -0.740738 -0.280088 -0.007739

           556       557       558       559       560  561  562
0    -0.464761 -0.018446 -0.841247  0.179941 -0.058627    1    5
1    -0.732626  0.703511 -0.844788  0.180289 -0.054317    1    5
2     0.100699  0.808529 -0.848933  0.180637 -0.049118    1    5
3     0.640011 -0.485366 -0.848649  0.181935 -0.047663    1    5
4     0.693578 -0.615971 -0.847865  0.185151 -0.043892    1    5
…          …         …         …         …         …  …  …
7347  0.206972 -0.425619 -0.791883  0.238604  0.049819   30    2
7348 -0.879033  0.400219 -0.771840  0.252676  0.050053   30    2
7349  0.864404  0.701169 -0.779133  0.249145  0.040811   30    2
7350  0.936674 -0.589479 -0.785181  0.246432  0.025339   30    2
7351 -0.056088 -0.616956 -0.783267  0.246809  0.036695   30    2

[7352 rows x 563 columns]
```

[4]:
```python
X_train = dataset_train.values[:, 0:561]
print("La dimension de X train est : {}".format(X_train.shape))
```

```
La dimension de X train est : (7352, 561)
```

[5]:
```python
y_train = dataset_train.values[:, 562]
print("La dimension de y train est : {}".format(y_train.shape))
```

```
La dimension de y train est : (7352,)
```

1.3.2 On importe les données de test

[6]:
```
dataset_test = pd.read_csv(path_dataset + "test/X_test_new.txt", sep=' ',␣
↪header=None)
dataset_test
```

[6]:
```
             0         1         2         3         4         5         6    \
0     0.257178 -0.023285 -0.014654 -0.938404 -0.920091 -0.667683 -0.952501
1     0.286027 -0.013163 -0.119083 -0.975415 -0.967458 -0.944958 -0.986799
2     0.275485 -0.026050 -0.118152 -0.993819 -0.969926 -0.962748 -0.994403
3     0.270298 -0.032614 -0.117520 -0.994743 -0.973268 -0.967091 -0.995274
4     0.274833 -0.027848 -0.129527 -0.993852 -0.967445 -0.978295 -0.994111
…          …        …        …        …        …        …        …
2942  0.310155 -0.053391 -0.099109 -0.287866 -0.140589 -0.215088 -0.356083
2943  0.363385 -0.039214 -0.105915 -0.305388  0.028148 -0.196373 -0.373540
2944  0.349966  0.030077 -0.115788 -0.329638 -0.042143 -0.250181 -0.388017
2945  0.237594  0.018467 -0.096499 -0.323114 -0.229775 -0.207574 -0.392380
2946  0.153627 -0.018437 -0.137018 -0.330046 -0.195253 -0.164339 -0.430974

             7         8         9    …       553       554       555  \
0    -0.925249 -0.674302 -0.894088  … -0.705974  0.006462  0.162920
1    -0.968401 -0.945823 -0.894088  … -0.594944 -0.083495  0.017500
2    -0.970735 -0.963483 -0.939260  … -0.640736 -0.034956  0.202302
3    -0.974471 -0.968897 -0.938610  … -0.736124 -0.017067  0.154438
4    -0.965953 -0.977346 -0.938610  … -0.846595 -0.002223 -0.040046
…          …        …        …  …       …        …        …
2942 -0.148775 -0.232057  0.185361  … -0.750809 -0.337422  0.346295
2943 -0.030036 -0.270237  0.185361  … -0.700274 -0.736701 -0.372889
2944 -0.133257 -0.347029  0.007471  … -0.467179 -0.181560  0.088574
2945 -0.279610 -0.289477  0.007471  … -0.617737  0.444558 -0.819188
2946 -0.218295 -0.229933 -0.111527  … -0.436940  0.598808 -0.287951

             556       557       558       559       560  561  562
0    -0.825886  0.271151 -0.720009  0.276801 -0.057978    2    5
1    -0.434375  0.920593 -0.698091  0.281343 -0.083898    2    5
2     0.064103  0.145068 -0.702771  0.280083 -0.079346    2    5
3     0.340134  0.296407 -0.698954  0.284114 -0.077108    2    5
4     0.736715 -0.118545 -0.692245  0.290722 -0.073857    2    5
…          …        …        …        …        …  …  …
2942  0.884904 -0.698885 -0.651732  0.274627  0.184784   24    2
2943 -0.657421  0.322549 -0.655181  0.273578  0.182412   24    2
2944  0.696663  0.363139 -0.655357  0.274479  0.181184   24    2
2945  0.929294 -0.008398 -0.659719  0.264782  0.187563   24    2
2946  0.876030 -0.024965 -0.660080  0.263936  0.188103   24    2

[2947 rows x 563 columns]
```

[7]:
```
X_test = dataset_test.values[:, 0:561]
print("La dimension de X test est : {}".format(X_test.shape))
```

```
La dimension de X test est : (2947, 561)
```

[8]:
```
y_test = dataset_test.values[:, 562]
print("La dimension de y test est : {}".format(y_test.shape))
```

```
La dimension de y test est : (2947,)
```

1.3.3 Utilisation de PCA pour réduire la dimension des données (Nous allons utiliser la librairie SKLearn)

[9]:
```
# choix du nombre de composantes à calculer
n_comp = X_train.shape[1]
print(n_comp)
```

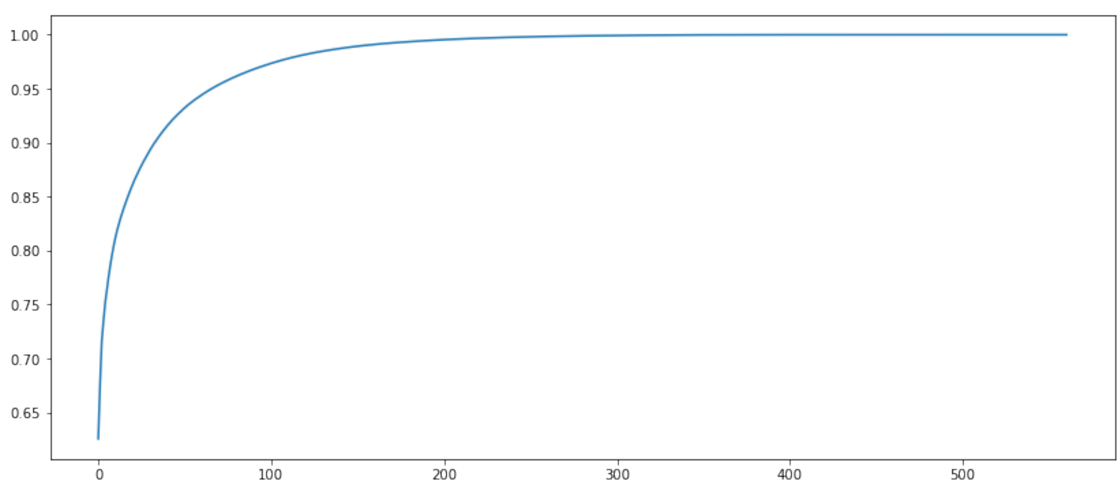
```
561
```

[10]:
```
# Calcul des composantes principales
pca = PCA(n_components=n_comp)
pca.fit(X_train)
```

[10]:
```
PCA(n_components=561)
```

[11]:
```
fig, axes = plt.subplots(nrows=1, ncols=1, figsize=(14, 6))
plt.plot(np.cumsum(pca.explained_variance_ratio_))
```

[11]:
```
[<matplotlib.lines.Line2D at 0x7f6e381d4970>]
```



[12]:
```python
np.argmax(np.cumsum(pca.explained_variance_ratio_) >= 0.99)
```

[12]: 154

[13]:
```python
print("Nous pouvons donc réduire à 155 dimension pour conserver 99% de la␣
↪variance")
```

Nous pouvons donc réduire à 155 dimension pour conserver 99% de la variance

[14]:
```python
# choix du nombre de composantes à calculer
n_comp = 155
```

[15]:
```python
# Calcul des composantes principales
pca = PCA(n_components=n_comp)
pca.fit(X_train)
```

[15]: PCA(n_components=155)

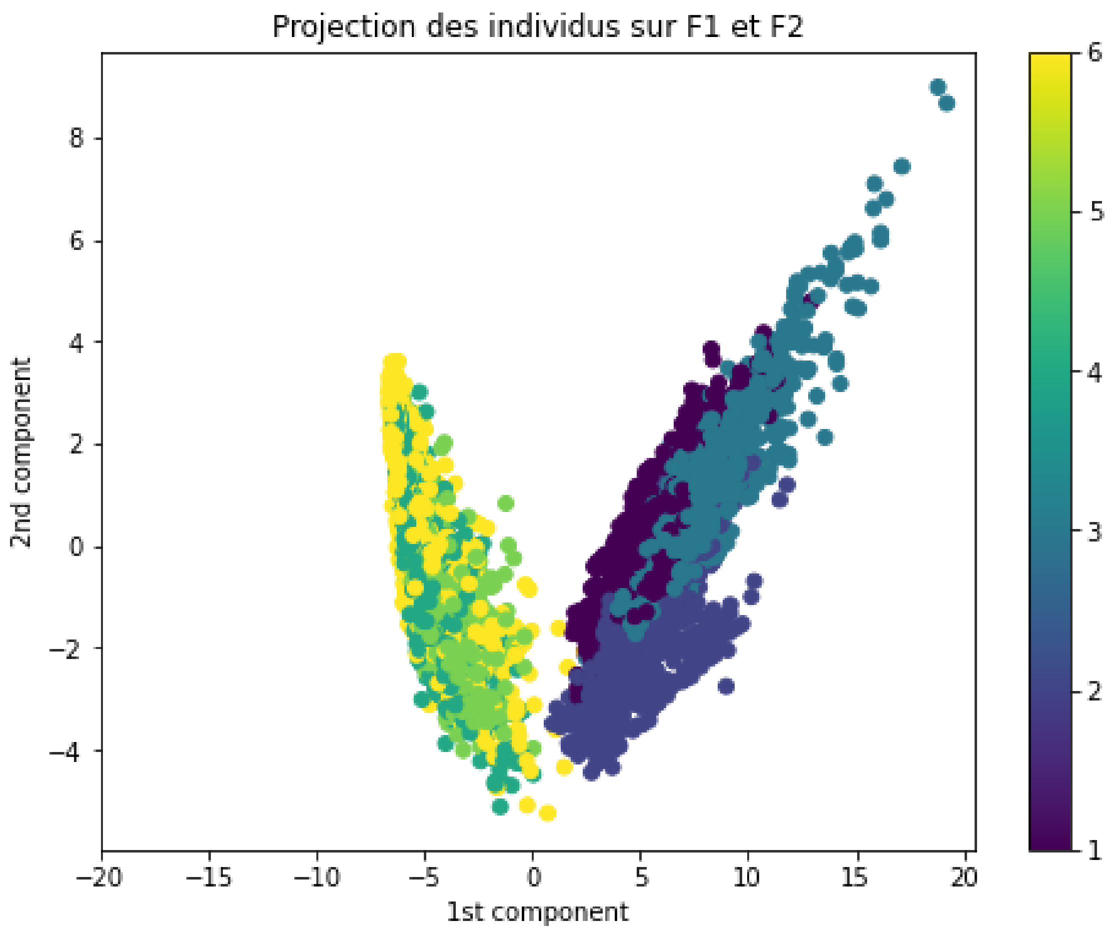
[16]:
```python
# Projection des individus
X_projected = pca.transform(X_train)
```

[17]:
```python
# Projection des composantes 1 et 2

plt.figure(figsize=(8,6))

plt.scatter(X_projected[:,0], X_projected[:,1], c=y_train)
plt.title('Projection des individus sur F1 et F2')
plt.xlim(-20)
plt.colorbar()
plt.xlabel("1st component")
plt.ylabel("2nd component")
```

[17]: Text(0, 0.5, '2nd component')



2 utilisation du modèle SVM pour la classification

[18]:
```
model_svm= make_pipeline(StandardScaler(), SVC())

params = {'svc__decision_function_shape': ['ovo', 'ovr'],
          'svc__gamma': ['auto', 'scale'],
          'svc__kernel': ['rbf', 'poly', 'linear']}

grid = GridSearchCV(model_svm, params, cv=5)

print(model_svm)
```

```
Pipeline(steps=[('standardscaler', StandardScaler()), ('svc', SVC())])
```

[19]:
```
# Formation du model
```

```
X_train_pca = pca.transform(X_train)

grid.fit(X_train_pca, y_train)
```

[19]:
```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('standardscaler', StandardScaler()),
                                       ('svc', SVC())]),
             param_grid={'svc__decision_function_shape': ['ovo', 'ovr'],
                         'svc__gamma': ['auto', 'scale'],
                         'svc__kernel': ['rbf', 'poly', 'linear']})
```

[20]:
```
# Affichage des meilleurs paramètres du modèle
grid.best_params_
```

[20]:
```
{'svc__decision_function_shape': 'ovo',
 'svc__gamma': 'auto',
 'svc__kernel': 'linear'}
```

[21]:
```
# Score sur les données d'entrainement
grid.score(X_train_pca, y_train)
```

[21]:
```
0.9946953210010882
```

[22]:
```
# Score sur les données de test

X_test_pca = pca.transform(X_test)

grid.score(X_test_pca, y_test)
```

[22]:
```
0.9582626399728538
```

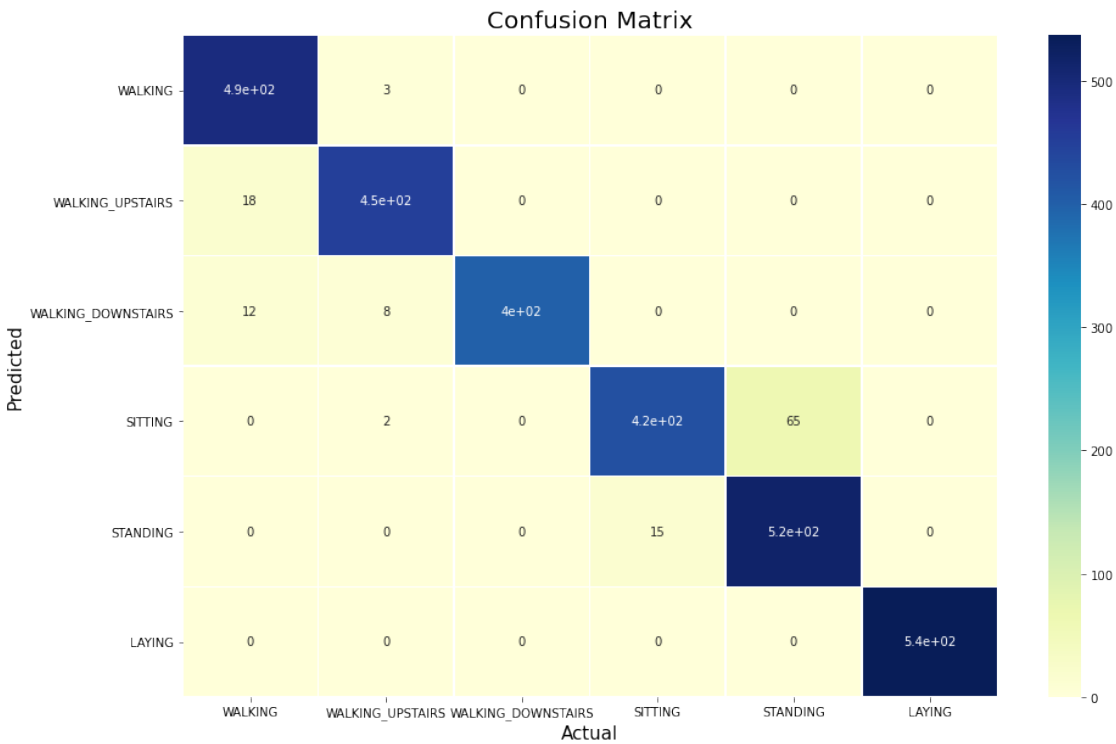
[23]:
```
# Matrice de confusion sur les données de test
confusion = confusion_matrix(y_test, grid.predict(X_test_pca))
confusion
```

[23]:
```
array([[493,   3,   0,   0,   0,   0],
       [ 18, 453,   0,   0,   0,   0],
       [ 12,   8, 400,   0,   0,   0],
       [  0,   2,   0, 424,  65,   0],
       [  0,   0,   0,  15, 517,   0],
       [  0,   0,   0,   0,   0, 537]])
```

[24]:
```
labels = ['WALKING', 'WALKING_UPSTAIRS', "WALKING_DOWNSTAIRS", "SITTING",␣
 ↪"STANDING", "LAYING"]

df_cm = pd.DataFrame(confusion, index = labels, columns = labels)
```

```
plt.figure(figsize = (15,10))
plt.title('Confusion Matrix', fontsize = 20)
sns.heatmap(df_cm, annot=True, cmap="YlGnBu", linewidths=.5)
plt.xlabel('Actual', fontsize = 15)
plt.ylabel('Predicted', fontsize = 15)
plt.show()
```




```
[ ]:
```