principal_component_analysis

July 24, 2020

0.1 Prepare modules and data.

[1]:
```
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegressionCV
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
```

[2]:
```
# read data.
cancer_df = pd.read_csv('data/cancer.csv')
```

[3]:
```
# cheack data shape.
print('cancer df shape: {}'.format(cancer_df.shape))
```

```
cancer df shape: (569, 33)
```

[4]:
```
# show data.
cancer_df.head(5)
```

[4]:
```
         id diagnosis  radius_mean  texture_mean  perimeter_mean  area_mean  \
0    842302         M        17.99         10.38          122.80     1001.0
1    842517         M        20.57         17.77          132.90     1326.0
2  84300903         M        19.69         21.25          130.00     1203.0
3  84348301         M        11.42         20.38           77.58      386.1
4  84358402         M        20.29         14.34          135.10     1297.0

   smoothness_mean  compactness_mean  concavity_mean  concave points_mean  \
0          0.11840           0.27760          0.3001              0.14710
1          0.08474           0.07864          0.0869              0.07017
2          0.10960           0.15990          0.1974              0.12790
3          0.14250           0.28390          0.2414              0.10520
4          0.10030           0.13280          0.1980              0.10430
```

```
   …  texture_worst  perimeter_worst  area_worst  smoothness_worst  \
0  …          17.33           184.60      2019.0            0.1622
1  …          23.41           158.80      1956.0            0.1238
2  …          25.53           152.50      1709.0            0.1444
3  …          26.50            98.87       567.7            0.2098
4  …          16.67           152.20      1575.0            0.1374

   compactness_worst  concavity_worst  concave points_worst  symmetry_worst  \
0             0.6656           0.7119                0.2654          0.4601
1             0.1866           0.2416                0.1860          0.2750
2             0.4245           0.4504                0.2430          0.3613
3             0.8663           0.6869                0.2575          0.6638
4             0.2050           0.4000                0.1625          0.2364

   fractal_dimension_worst  Unnamed: 32
0                  0.11890          NaN
1                  0.08902          NaN
2                  0.08758          NaN
3                  0.17300          NaN
4                  0.07678          NaN

[5 rows x 33 columns]
```

[5]:
```
# delete unnecessary data.
cancer_df.drop('Unnamed: 32', axis=1, inplace=True)
```

[6]:
```
# extracting the target variable
y = cancer_df.diagnosis.apply(lambda d: 1 if d == 'M' else 0)
```

[7]:
```
# extracting explanatory variables
X = cancer_df.loc[:, 'radius_mean':]
```

[8]:
```
# split the data.
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)
```

[9]:
```
# standardize data.
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[10]:
```
# Logistic regression.
logistic = LogisticRegressionCV(cv=10, random_state=0, max_iter=1000)
logistic.fit(X_train_scaled, y_train)
```

[10]:
```
LogisticRegressionCV(Cs=10, class_weight=None, cv=10, dual=False,
                     fit_intercept=True, intercept_scaling=1.0, l1_ratios=None,
                     max_iter=1000, multi_class='auto', n_jobs=None,
```

```
                        penalty='l2', random_state=0, refit=True, scoring=None,
                        solver='lbfgs', tol=0.0001, verbose=0)
```

[11]:

```
# verification
print('Train score: {:.3f}'.format(logistic.score(X_train_scaled, y_train)))
print('Test score: {:.3f}'.format(logistic.score(X_test_scaled, y_test)))
print('Confustion matrix:\n{}'.format(confusion_matrix(y_true=y_test,␣
 ↪y_pred=logistic.predict(X_test_scaled))))
```

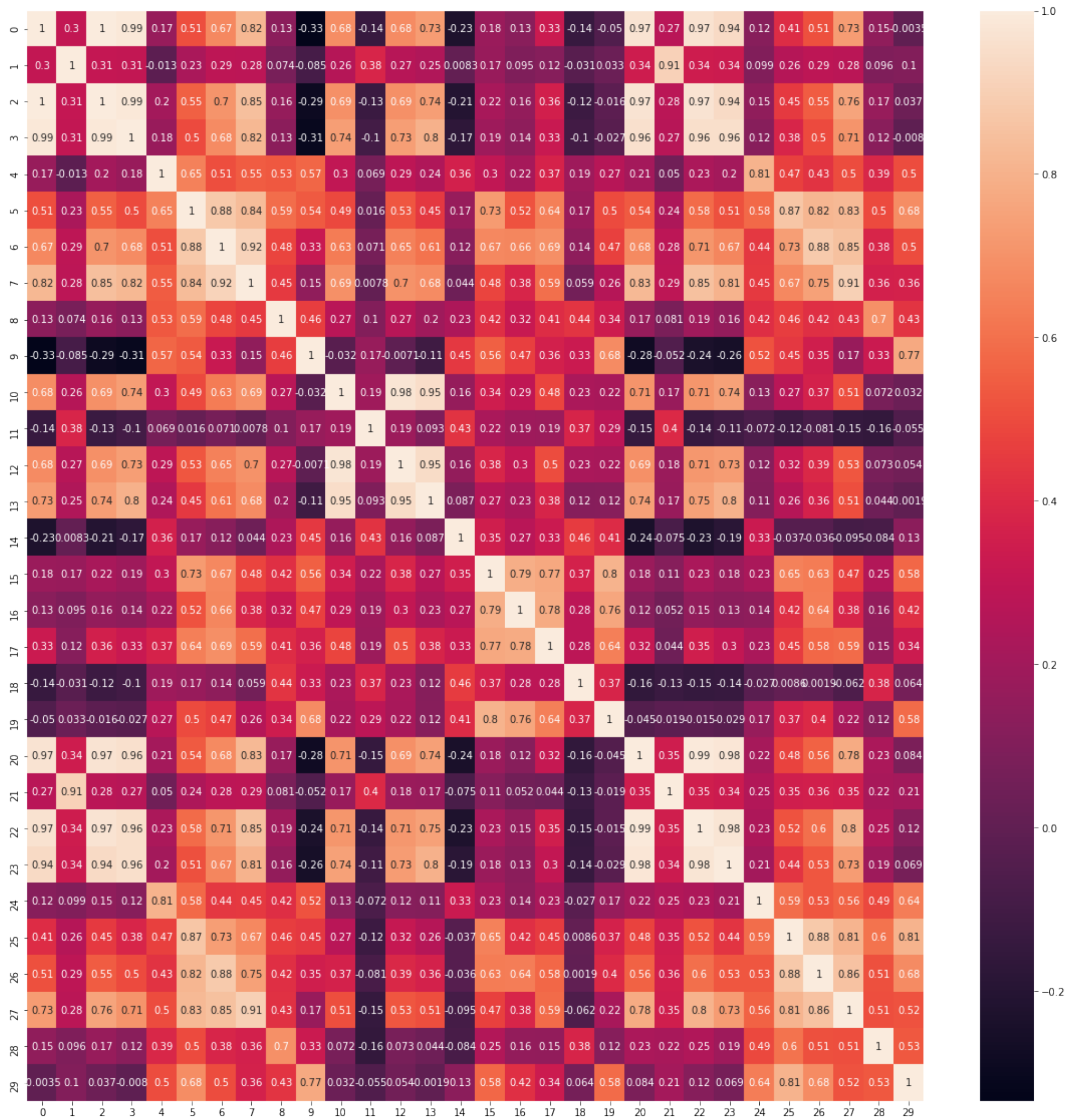
```
Train score: 0.988
Test score: 0.972
Confustion matrix:
[[89  1]
 [ 3 50]]
```

[12]:

```
# Draw correlations between variables.
plt.figure(figsize=(20, 20))
seaborn.heatmap(pd.DataFrame(X_train_scaled).corr(), annot=True)
```

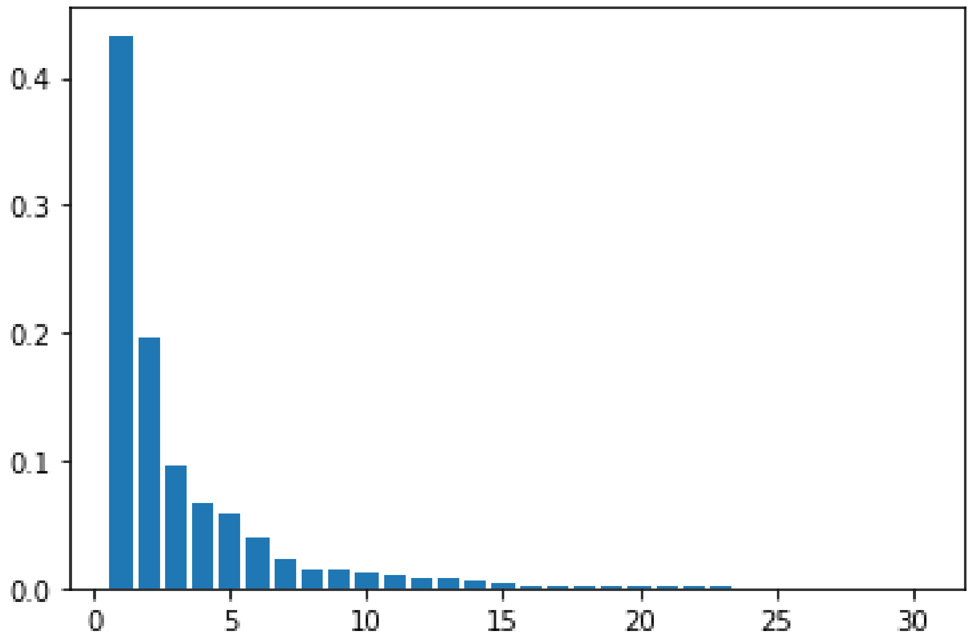
[12]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f3b80776750>
```



[13]:
```
# Principal component analysis is performed with a dimensionality of 30.
pca = PCA(n_components=30)
pca.fit(X_train_scaled)
plt.bar([n for n in range(1, len(pca.explained_variance_ratio_)+1)], pca.
 ↪explained_variance_ratio_)
```

[13]: <BarContainer object of 30 artists>



[14]:
```
# Compression to dimension 2
pca = PCA(n_components=2)
X_train_pca = pca.fit_transform(X_train_scaled)
print('X_train_pca shape: {}'.format(X_train_pca.shape))
```

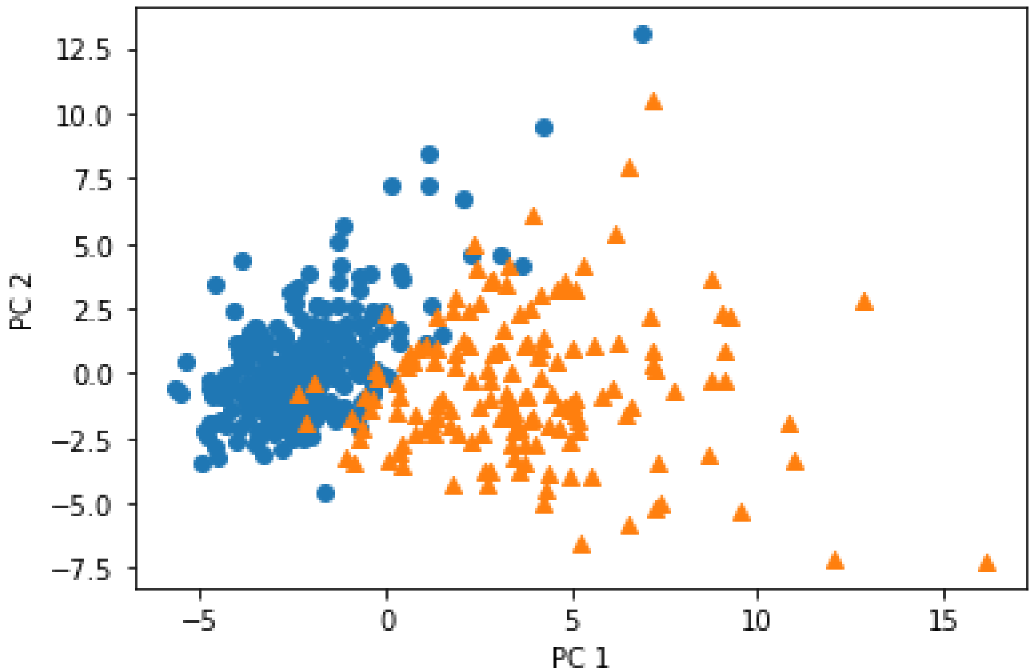
```
X_train_pca shape: (426, 2)
```

[15]:
```
# contribution rate
print('explained variance ratio: {}'.format(pca.explained_variance_ratio_))
# explained variance ratio: [ 0.43315126  0.19586506]
```

```
explained variance ratio: [0.43315126 0.19586506]
```

[16]:
```
# Plotted on a scatter plot
temp = pd.DataFrame(X_train_pca)
temp['Outcome'] = y_train.values
b = temp[temp['Outcome'] == 0]
m = temp[temp['Outcome'] == 1]
plt.scatter(x=b[0], y=b[1], marker='o')
plt.scatter(x=m[0], y=m[1], marker='^')
plt.xlabel('PC 1')
plt.ylabel('PC 2')
```

[16]:
```
Text(0, 0.5, 'PC 2')
```




```
[17]: # Creating a Pipeline
      pca_pipeline = Pipeline([
          ('scale', StandardScaler()),
          ('decomposition', PCA(n_components=2)),
          ('model', LogisticRegressionCV(cv=10, random_state=0))
      ])
```

```
[18]: # Standardization, dimensional compression and learning
      pca_pipeline.fit(X_train, y_train)
```

```
[18]: Pipeline(memory=None,
               steps=[('scale',
                       StandardScaler(copy=True, with_mean=True, with_std=True)),
                      ('decomposition',
                       PCA(copy=True, iterated_power='auto', n_components=2,
                           random_state=None, svd_solver='auto', tol=0.0,
                           whiten=False)),
                      ('model',
                       LogisticRegressionCV(Cs=10, class_weight=None, cv=10,
                                            dual=False, fit_intercept=True,
                                            intercept_scaling=1.0, l1_ratios=None,
                                            max_iter=100, multi_class='auto',
                                            n_jobs=None, penalty='l2', random_state=0,
                                            refit=True, scoring=None, solver='lbfgs',
                                            tol=0.0001, verbose=0))],
```

```
verbose=False)
```

[19]:
```
# verification
print('Train score: {:.3f}'.format(pca_pipeline.score(X_train, y_train)))
print('Test score: {:.3f}'.format(pca_pipeline.score(X_test, y_test)))
print('Confustion matrix:\n{}'.format(confusion_matrix(y_true=y_test,␣
↪y_pred=pca_pipeline.predict(X_test))))
```

```
Train score: 0.965
Test score: 0.937
Confustion matrix:
[[84  6]
 [ 3 50]]
```

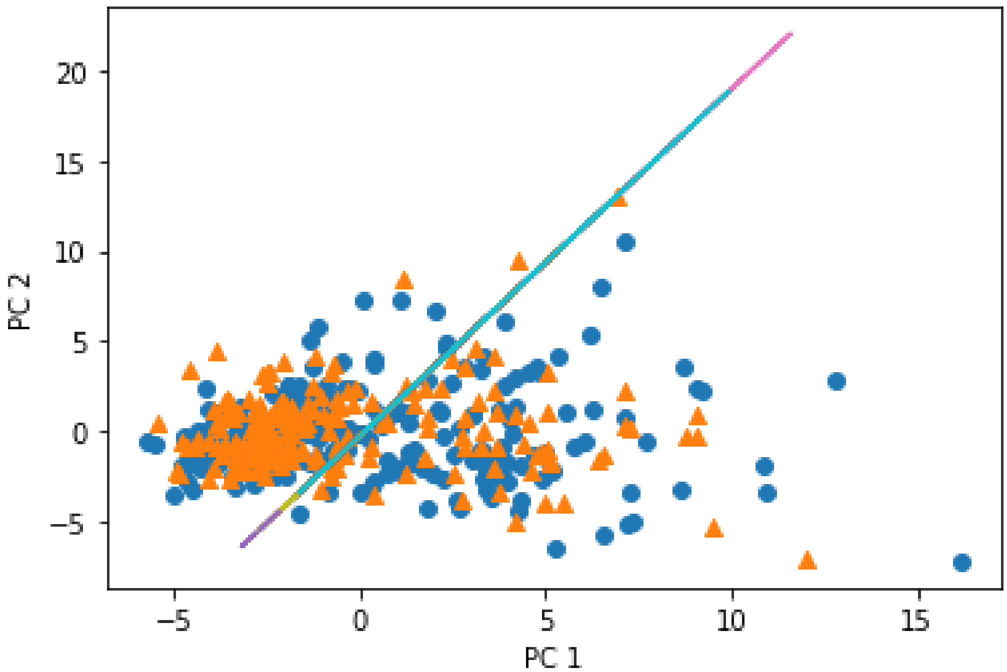
[20]:
```
# Intercept and slope
intercept = pca_pipeline.steps[2][1].intercept_
coef = pca_pipeline.steps[2][1].coef_
print('model intercept: {}'.format(intercept))
print('model coef : {}'.format(coef))

# Plot the decision boundary
plt.plot(X_train_scaled, -(X_train_scaled*coef[0][0] + intercept[0])/coef[0][1])
print('y = x*{} + {}'.format(-coef[0][0]/coef[0][1], -intercept[0]/coef[0][1]))

# Plotted on a scatter plot
temp = pd.DataFrame(X_train_pca)
temp['Outcome'] = y
b = temp[temp['Outcome'] == 0]
m = temp[temp['Outcome'] == 1]
plt.scatter(x=b[0], y=b[1], marker='o')
plt.scatter(x=m[0], y=m[1], marker='^')
plt.xlabel('PC 1')
plt.ylabel('PC 2')
```

```
model intercept: [-0.30694316]
model coef : [[ 1.78050858 -0.92218849]]
y = x*1.9307425785710486 + -0.3328421076224521
```

[20]:
```
Text(0, 0.5, 'PC 2')
```



20
15
10
5
0
−5
PC 2
−5
0
5
10
15
PC 1