PCA - Principal Component Analisys - Redução de Dimensionalidade

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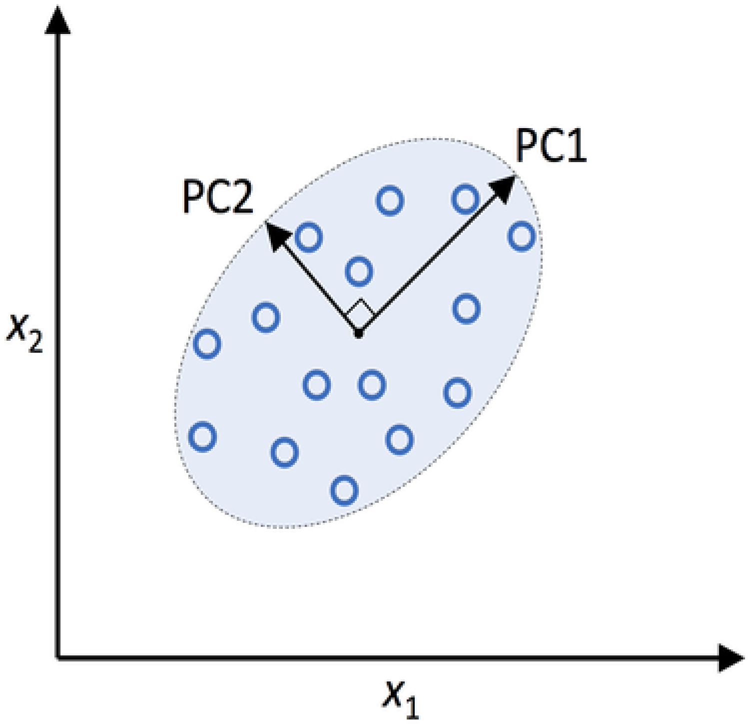
Passos Principais - PCA - principal component analysis

In [1]:

```
from PIL import Image
img = Image.open('image01.png') #, width=400)
width  = 400
height = 400
img = img.resize((width, height), Image.ANTIALIAS)
img
```

Out[1]:



Extraindo os componentes principais passo-a-passo

In [2]:

```
import pandas as pd

df_wine = pd.read_csv('wine.data',
                      header=None)

df_wine.columns = ['Class label', 'Alcohol', 'Malic acid', 'Ash',
                   'Alcalinity of ash', 'Magnesium', 'Total phenols',
                   'Flavanoids', 'Nonflavanoid phenols', 'Proanthocyanins',
                   'Color intensity', 'Hue',
                   'OD280/OD315 of diluted wines', 'Proline']

df_wine.head()
```

Out[2]:

	Class label	Alcohol	Malic acid	Ash	Alcalinity of ash	Magnesium	Total phenols	Flavanoids	Nonflavanoid phenols	P
0	1	14.23	1.71	2.43	15.6	127	2.80	3.06	0.28	
1	1	13.20	1.78	2.14	11.2	100	2.65	2.76	0.26	
2	1	13.16	2.36	2.67	18.6	101	2.80	3.24	0.30	
3	1	14.37	1.95	2.50	16.8	113	3.85	3.49	0.24	
4	1	13.24	2.59	2.87	21.0	118	2.80	2.69	0.39	

In [3]:

```
print('Número de dimensões:', len(df_wine.columns)-1)
```

```
Número de dimensões: 13
```

In [4]:

```
# conta o número de ocorrencia de cada classe
df_wine['Class label'].value_counts()
```

Out[4]:

```
2    71
1    59
3    48
Name: Class label, dtype: int64
```

Splitting de dados: 70% treino e 30% teste

In [5]:

```
from sklearn.model_selection import train_test_split

X= df_wine.iloc[:, 1:].values
y = df_wine.iloc[:, 0].values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
                     stratify=y,
                     random_state=0)
```

In [6]:

```
X_train[:3]
```

Out[6]:

```
array([[1.362e+01, 4.950e+00, 2.350e+00, 2.000e+01, 9.200e+01, 2.000
e+00,
        8.000e-01, 4.700e-01, 1.020e+00, 4.400e+00, 9.100e-01, 2.050
e+00,
        5.500e+02],
       [1.376e+01, 1.530e+00, 2.700e+00, 1.950e+01, 1.320e+02, 2.950
e+00,
        2.740e+00, 5.000e-01, 1.350e+00, 5.400e+00, 1.250e+00, 3.000
e+00,
        1.235e+03],
       [1.373e+01, 1.500e+00, 2.700e+00, 2.250e+01, 1.010e+02, 3.000
e+00,
        3.250e+00, 2.900e-01, 2.380e+00, 5.700e+00, 1.190e+00, 2.710
e+00,
        1.285e+03]])
```

In [7]:

```
y_train[:3]
```

Out[7]:

```
array([3, 1, 1], dtype=int64)
```

Colocando o dado em Escala (Normalizando)

In [8]:

```
X_train.min(), X_train.max()
```

Out[8]:

```
(0.13, 1680.0)
```

In [9]:

```
from sklearn.preprocessing import StandardScaler

sc = StandardScaler()
X_train_std = sc.fit_transform(X_train)
X_test_std = sc.transform(X_test)
```

In [10]:

```
X_train_std.min(), X_train_std.max()
```

Out[10]:

```
(-2.55493448916567, 3.6932366525105946)
```

In [11]:

```
X_train_std[:3]
```

Out[11]:

```
array([[ 0.71225893,  2.22048673, -0.13025864,  0.05962872, -0.50432
733,
        -0.52831584, -1.24000033,  0.84118003, -1.05215112, -0.29218
864,
        -0.20017028, -0.82164144, -0.62946362],
       [ 0.88229214, -0.70457155,  1.17533605, -0.09065504,  2.34147
876,
         1.01675879,  0.66299475,  1.0887425 , -0.49293533,  0.13152
077,
         1.33982592,  0.54931269,  1.47568796],
       [ 0.84585645, -0.73022996,  1.17533605,  0.81104754,  0.13597
904,
         1.09807851,  1.16326665, -0.64419483,  1.25249578,  0.25863
359,
         1.06806189,  0.1308109 ,  1.62934866]])
```

A matriz de covariância

Covariância, ou variância conjunta, é uma medida do grau de interdependência (ou inter-relação) numérica entre duas variáveis aleatórias. Assim, variáveis independentes têm covariância zero.
A covariância é por vezes chamada de medida de dependência linear entre as duas variáveis aleatórias.
O Coeficiente de Correlação Linear é um conceito relacionado usado para medir o grau de dependência linear entre duas variáveis, variando entre -1 e 1, indicando o sentido da dependência.

In [12]:

```
import numpy as np
cov_mat = np.cov(X_train_std.T)
```

In [13]:

```
len(cov_mat)
```

Out[13]:

```
13
```

In [14]:

```
cov_mat
```

Out[14]:

```
array([[ 1.00813008,  0.06709556,  0.17405351, -0.35439069,  0.26374
703,
         0.29079481,  0.21835807, -0.08111974,  0.10436705,  0.54282
846,
         0.05893536, -0.01797029,  0.6415292 ],
       [ 0.06709556,  1.00813008,  0.08326463,  0.26356776, -0.11349
172,
        -0.33735555, -0.41035281,  0.33653916, -0.21602672,  0.17504
154,
        -0.551593  , -0.40561695, -0.24089991],
       [ 0.17405351,  0.08326463,  1.00813008,  0.46420355,  0.29092
834,
         0.18020384,  0.15537535,  0.15918823, -0.00703776,  0.20549
146,
         0.00665422,  0.02039019,  0.223495  ],
       [-0.35439069,  0.26356776,  0.46420355,  1.00813008, -0.07406
447,
        -0.28060672, -0.31391899,  0.31581353, -0.24621059, -0.08872
685,
        -0.22595587, -0.16799906, -0.46393412],
       [ 0.26374703, -0.11349172,  0.29092834, -0.07406447,  1.00813
008,
         0.25667578,  0.21025773, -0.26003426,  0.19601657,  0.20606
456,
         0.13359768,  0.06633258,  0.41810999],
       [ 0.29079481, -0.33735555,  0.18020384, -0.28060672,  0.25667
578,
         1.00813008,  0.87123661, -0.44979792,  0.62334099, -0.05689
854,
         0.50664086,  0.71978745,  0.52986924],
       [ 0.21835807, -0.41035281,  0.15537535, -0.31391899,  0.21025
773,
         0.87123661,  1.00813008, -0.54824079,  0.64800868, -0.15864
896,
         0.60417124,  0.79319622,  0.52836141],
       [-0.08111974,  0.33653916,  0.15918823,  0.31581353, -0.26003
426,
        -0.44979792, -0.54824079,  1.00813008, -0.39989328,  0.19810
581,
        -0.36629252, -0.57622953, -0.34099709],
       [ 0.10436705, -0.21602672, -0.00703776, -0.24621059,  0.19601
657,
         0.62334099,  0.64800868, -0.39989328,  1.00813008, -0.00330
144,
         0.32019524,  0.50615495,  0.32976133],
       [ 0.54282846,  0.17504154,  0.20549146, -0.08872685,  0.20606
456,
        -0.05689854, -0.15864896,  0.19810581, -0.00330144,  1.00813
008,
        -0.45834115, -0.4666752 ,  0.32156154],
       [ 0.05893536, -0.551593  ,  0.00665422, -0.22595587,  0.13359
768,
         0.50664086,  0.60417124, -0.36629252,  0.32019524, -0.45834
115,
         1.00813008,  0.6435365 ,  0.35356248],
       [-0.01797029, -0.40561695,  0.02039019, -0.16799906,  0.06633
258,
         0.71978745,  0.79319622, -0.57622953,  0.50615495, -0.46667
52 ,
```

```
         0.6435365 ,  1.00813008,  0.26670793],
       [ 0.6415292 , -0.24089991,  0.223495  , -0.46393412,  0.41810
999,
         0.52986924,  0.52836141, -0.34099709,  0.32976133,  0.32156
154,
         0.35356248,  0.26670793,  1.00813008]])
```

Decomposição da matriz de covariância em AutoVetores (eingenvectors)

OS eigenvectors (Autovetores) da matriz de covariância, representam os Componentes Principais, que são as direções de máxima variância.
Os eingenvalues, que são os Autovalores, são valores associados com os Autovetores v, definem a magnitude.

In [15]:

```
eigen_vals, eigen_vecs = np.linalg.eig(cov_mat)
print('\nAutovalores \n%s' % eigen_vals)
```

```
Autovalores
[4.84274532 2.41602459 1.54845825 0.96120438 0.84166161 0.6620634
 0.51828472 0.34650377 0.3131368  0.10754642 0.21357215 0.15362835
 0.1808613 ]
```

In [16]:

```
print('\nAutovetores \n%s' % eigen_vecs)
```

```
Autovetores
[[-1.37242175e-01  5.03034778e-01 -1.37748734e-01 -3.29610003e-03
  -2.90625226e-01  2.99096847e-01  7.90529293e-02 -3.68176414e-01
  -3.98377017e-01 -9.44869777e-02  3.74638877e-01 -1.27834515e-01
   2.62834263e-01]
 [ 2.47243265e-01  1.64871190e-01  9.61503863e-02  5.62646692e-01
   8.95378697e-02  6.27036396e-01 -2.74002014e-01 -1.25775752e-02
   1.10458230e-01  2.63652406e-02 -1.37405597e-01  8.06401578e-02
  -2.66769211e-01]
 [-2.54515927e-02  2.44564761e-01  6.77775667e-01 -1.08977111e-01
  -1.60834991e-01  3.89128239e-04  1.32328045e-01  1.77578177e-01
   3.82496856e-01  1.42747511e-01  4.61583035e-01  1.67924873e-02
  -1.15542548e-01]
 [ 2.06945084e-01 -1.13529045e-01  6.25040550e-01  3.38187002e-02
   5.15873402e-02 -4.05836452e-02  2.23999097e-01 -4.40592110e-01
  -2.43373853e-01 -1.30485780e-01 -4.18953989e-01 -1.10845657e-01
   1.99483410e-01]
 [-1.54365821e-01  2.89745182e-01  1.96135481e-01 -3.67511070e-01
   6.76487073e-01  6.57772614e-02 -4.05268966e-01  1.16617503e-01
  -2.58982359e-01 -6.76080782e-02  1.00470630e-02  7.93879562e-02
   2.89018810e-02]
 [-3.93769523e-01  5.08010391e-02  1.40310572e-01  2.40245127e-01
  -1.18511144e-01 -5.89776247e-02 -3.47419412e-02  3.50192127e-01
  -3.42312860e-01  4.59917661e-01 -2.21254241e-01 -4.91459313e-01
  -6.63868598e-02]
 [-4.17351064e-01 -2.28733792e-02  1.17053859e-01  1.87053299e-01
  -1.07100349e-01 -3.01103180e-02  4.17835724e-02  2.18718183e-01
  -3.61231642e-02 -8.14583947e-01 -4.17513600e-02 -5.03074004e-02
  -2.13349079e-01]
 [ 3.05728961e-01  9.04888470e-02  1.31217777e-01 -2.29262234e-02
  -5.07581610e-01 -2.71728086e-01 -6.31145686e-01  1.97129425e-01
  -1.71436883e-01 -9.57480885e-02 -8.87569452e-02  1.75328030e-01
   1.86391279e-01]
 [-3.06683469e-01  8.35232677e-03  3.04309008e-02  4.96262330e-01
   2.01634619e-01 -4.39997519e-01 -3.23122775e-01 -4.33055871e-01
   2.44370210e-01  6.72468934e-02  1.99921861e-01 -3.67595797e-03
   1.68082985e-01]
 [ 7.55406578e-02  5.49775805e-01 -7.99299713e-02  1.06482939e-01
   5.73607091e-03 -4.11743459e-01  2.69082623e-01 -6.68411823e-02
  -1.55514919e-01  8.73336218e-02 -2.21668868e-01  3.59756535e-01
  -4.66369031e-01]
 [-3.26132628e-01 -2.07164328e-01  5.30591506e-02 -3.69053747e-01
  -2.76914216e-01  1.41673377e-01 -3.02640661e-01 -4.59762295e-01
   2.11961247e-02  1.29061125e-01 -9.84694573e-02  4.04669797e-02
  -5.32483880e-01]
 [-3.68610222e-01 -2.49025357e-01  1.32391030e-01  1.42016088e-01
  -6.66275572e-02  1.75842384e-01  1.30540143e-01  1.10827548e-01
  -2.38089559e-01  1.87646268e-01  1.91205783e-02  7.42229543e-01
   2.37835283e-01]
 [-2.96696514e-01  3.80229423e-01 -7.06502178e-02 -1.67682173e-01
  -1.28029045e-01  1.38018388e-01  8.11335043e-04  5.60817288e-03
   5.17278463e-01  1.21112574e-02 -5.42532072e-01  3.87395209e-02
   3.67763359e-01]]
```

Total e variância explicada

In [17]:

```
tot = sum(eigen_vals)
tot
```

Out[17]:

```
13.105691056910565
```

In [18]:

```
tot = sum(eigen_vals)
var_exp = [(i / tot) for i in sorted(eigen_vals, reverse=True)]
print("variância explicade de cada componente\n", var_exp)
```

```
variância explicade de cada componente
 [0.36951468599607645, 0.18434927059884165, 0.11815159094596986, 0.0
7334251763785471, 0.06422107821731672, 0.05051724484907654, 0.039546
53891241449, 0.026439183169220035, 0.02389319259185293, 0.0162961377
37251016, 0.013800211221948418, 0.01172226244308596, 0.0082060856790
91375]
```

In [19]:

```
sum(var_exp)
```

Out[19]:

```
1.0
```

In [20]:

```
cum_var_exp = np.cumsum(var_exp)
cum_var_exp
```

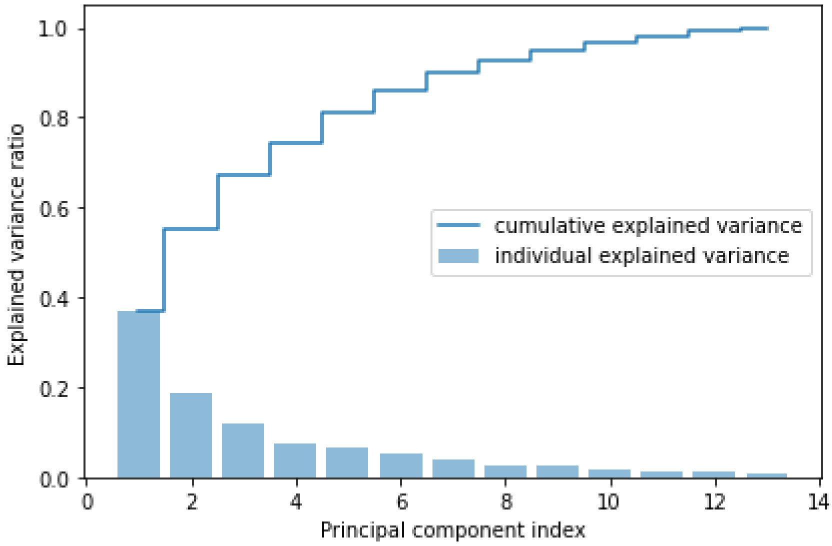
Out[20]:

```
array([0.36951469, 0.55386396, 0.67201555, 0.74535807, 0.80957914,
       0.86009639, 0.89964293, 0.92608211, 0.9499753 , 0.96627144,
       0.98007165, 0.99179391, 1.        ])
```

In [21]:

```
import matplotlib.pyplot as plt

plt.bar(range(1, 14), var_exp, alpha=0.5, align='center',
        label='individual explained variance')
plt.step(range(1, 14), cum_var_exp, where='mid',
         label='cumulative explained variance')
plt.ylabel('Explained variance ratio')
plt.xlabel('Principal component index')
plt.legend(loc='best')
plt.tight_layout()
plt.show()
```



Feature transformation - Criação de pares (AutoValores, AutoVetores)

In [22]:

```
# Make a list of (eigenvalue, eigenvector) tuples
eigen_pairs = [(np.abs(eigen_vals[i]), eigen_vecs[:, i])
               for i in range(len(eigen_vals))]

# Sort the (eigenvalue, eigenvector) tuples from high to low
eigen_pairs.sort(key=lambda k: k[0], reverse=True)
```

In [23]:

```
print('AutoValor - AutoVetor associado')
eigen_pairs[0:2]
```

```
AutoValor - AutoVetor associado
```

Out[23]:

```
[(4.842745315655895,
  array([-0.13724218,  0.24724326, -0.02545159,  0.20694508, -0.1543
6582,
         -0.39376952, -0.41735106,  0.30572896, -0.30668347,  0.0755
4066,
         -0.32613263, -0.36861022, -0.29669651])),
 (2.416024587035225,
  array([ 0.50303478,  0.16487119,  0.24456476, -0.11352904,  0.2897
4518,
          0.05080104, -0.02287338,  0.09048885,  0.00835233,  0.5497
7581,
         -0.20716433, -0.24902536,  0.38022942]))]
```

Matriz de transformação w (transformando para 2 dimensões)

In [24]:

```
w = np.hstack((eigen_pairs[0][1][:, np.newaxis],
               eigen_pairs[1][1][:, np.newaxis]))
print('Matrix Transformação W:\n', w)
```

```
Matrix Transformação W:
 [[-0.13724218  0.50303478]
 [ 0.24724326  0.16487119]
 [-0.02545159  0.24456476]
 [ 0.20694508 -0.11352904]
 [-0.15436582  0.28974518]
 [-0.39376952  0.05080104]
 [-0.41735106 -0.02287338]
 [ 0.30572896  0.09048885]
 [-0.30668347  0.00835233]
 [ 0.07554066  0.54977581]
 [-0.32613263 -0.20716433]
 [-0.36861022 -0.24902536]
 [-0.29669651  0.38022942]]
```

In [25]:

```
X_train_std[0]
```

Out[25]:

```
array([ 0.71225893,  2.22048673, -0.13025864,  0.05962872, -0.504327
33,
       -0.52831584, -1.24000033,  0.84118003, -1.05215112, -0.292188
64,
       -0.20017028, -0.82164144, -0.62946362])
```

In [26]:

```
X_train_std[0].dot(w)
```

Out[26]:

```
array([2.38299011, 0.45458499])
```

tranformando 13 dimensões (atributos) em 2 dimensões (atributos)

In [27]:

```
X_train_std[:3]
```

Out[27]:

```
array([[ 0.71225893,  2.22048673, -0.13025864,  0.05962872, -0.50432
733,
        -0.52831584, -1.24000033,  0.84118003, -1.05215112, -0.29218
864,
        -0.20017028, -0.82164144, -0.62946362],
       [ 0.88229214, -0.70457155,  1.17533605, -0.09065504,  2.34147
876,
         1.01675879,  0.66299475,  1.0887425 , -0.49293533,  0.13152
077,
         1.33982592,  0.54931269,  1.47568796],
       [ 0.84585645, -0.73022996,  1.17533605,  0.81104754,  0.13597
904,
         1.09807851,  1.16326665, -0.64419483,  1.25249578,  0.25863
359,
         1.06806189,  0.1308109 ,  1.62934866]])
```

In [28]:

```
X_train_pca = X_train_std.dot(w)
X_train_pca[:3]
```

Out[28]:

```
array([[ 2.38299011,  0.45458499],
       [-1.96578183,  1.65376939],
       [-2.53907598,  1.02909066]])
```

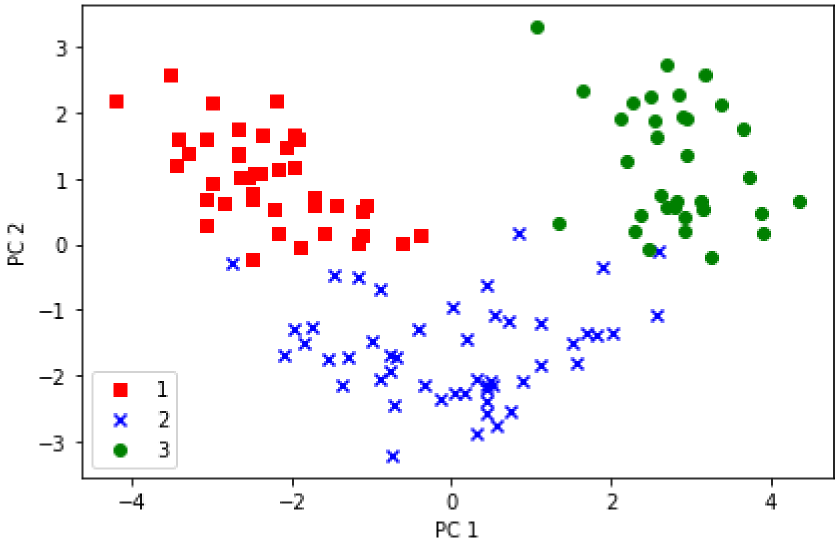
Plotando as 2 dimensões (PC1, PC2) e os classes (labels)

In [29]:

```
colors = ['r', 'b', 'g']
markers = ['s', 'x', 'o']

for l, c, m in zip(np.unique(y_train), colors, markers):
    plt.scatter(X_train_pca[y_train == l, 0],
                X_train_pca[y_train == l, 1],
                c=c, label=l, marker=m)

plt.xlabel('PC 1')
plt.ylabel('PC 2')
plt.legend(loc='lower left')
plt.tight_layout()
plt.show()
```



Principal component analysis (Pacote scikit-learn)

In [30]:

```
from sklearn.decomposition import PCA

pca = PCA()
X_train_pca = pca.fit_transform(X_train_std)
print("Variância explicada de cada dimensão\n",pca.explained_variance_ratio_)
```

```
Variância explicada de cada dimensão
 [0.36951469 0.18434927 0.11815159 0.07334252 0.06422108 0.05051724
 0.03954654 0.02643918 0.02389319 0.01629614 0.01380021 0.01172226
 0.00820609]
```

In [31]:

```
np.sum(pca.explained_variance_ratio_)
```

Out[31]:

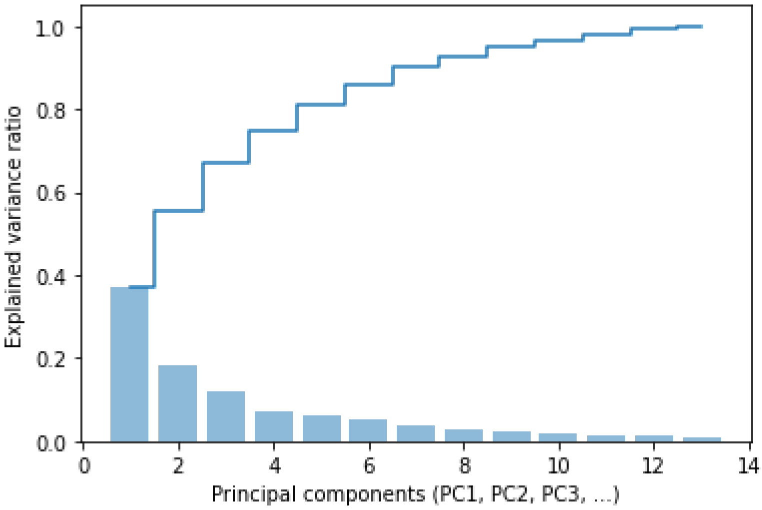
```
1.0
```

In [32]:

```
import matplotlib.pyplot as plt
import numpy as np

plt.bar(range(1, 14), pca.explained_variance_ratio_, alpha=0.5, align='center')
plt.step(range(1, 14), np.cumsum(pca.explained_variance_ratio_), where='mid')
plt.ylabel('Explained variance ratio')
plt.xlabel('Principal components (PC1, PC2, PC3, ...)')

plt.show()
```



PCA - transformando em 2 componentes

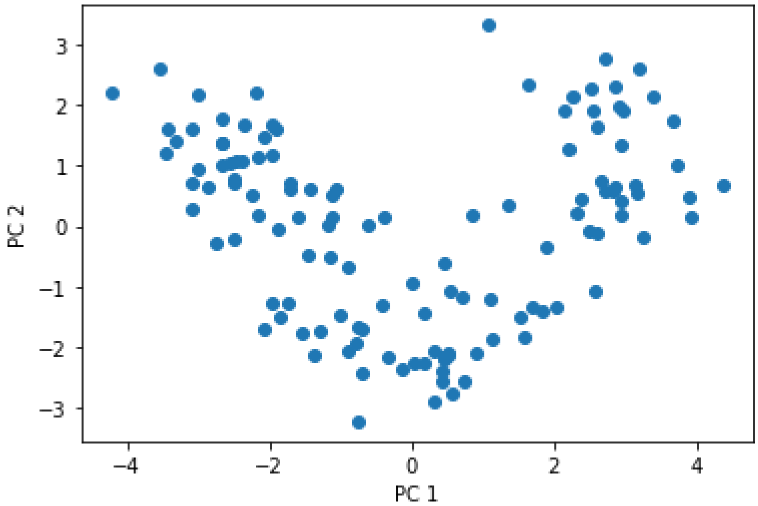
In [33]:

```
pca = PCA(n_components=2)
X_train_pca = pca.fit_transform(X_train_std)
X_test_pca = pca.transform(X_test_std)
print('Variância Explicada:\nPC1 = ',pca.explained_variance_ratio_[0], ', PC2 =
 ',pca.explained_variance_ratio_[1])
```

```
Variância Explicada:
PC1 =  0.36951468599607673 , PC2 =  0.18434927059884115
```

In [34]:

```
plt.scatter(X_train_pca[:, 0], X_train_pca[:, 1])
plt.xlabel('PC 1')
plt.ylabel('PC 2')
plt.show()
```



In [35]:

```
from matplotlib.colors import ListedColormap

def plot_decision_regions(X, y, classifier, resolution=0.02):

    # setup marker generator and color map
    markers = ('s', 'x', 'o', '^', 'v')
    colors = ('red', 'blue', 'lightgreen', 'gray', 'cyan')
    cmap = ListedColormap(colors[:len(np.unique(y))])

    # plot the decision surface
    x1_min, x1_max = X[:, 0].min() - 1, X[:, 0].max() + 1
    x2_min, x2_max = X[:, 1].min() - 1, X[:, 1].max() + 1
    xx1, xx2 = np.meshgrid(np.arange(x1_min, x1_max, resolution),
                           np.arange(x2_min, x2_max, resolution))
    Z = classifier.predict(np.array([xx1.ravel(), xx2.ravel()]).T)
    Z = Z.reshape(xx1.shape)
    plt.contourf(xx1, xx2, Z, alpha=0.4, cmap=cmap)
    plt.xlim(xx1.min(), xx1.max())
    plt.ylim(xx2.min(), xx2.max())

    # plot class samples
    for idx, cl in enumerate(np.unique(y)):
        plt.scatter(x=X[y == cl, 0],
                    y=X[y == cl, 1],
                    alpha=0.6,
                    c=cmap(idx),
                    edgecolor='black',
                    marker=markers[idx],
                    label=cl)
    plt.xlabel('PC 1')
    plt.ylabel('PC 2')
    plt.legend(loc='lower left')
    plt.tight_layout()
```

Treinando um Classificador de Regressão Logística - 2 Componentes Principais (PC1, PC2)

In [36]:

```
from sklearn.linear_model import LogisticRegression

pca = PCA(n_components=2)
X_train_pca = pca.fit_transform(X_train_std)
X_test_pca = pca.transform(X_test_std)
print('Variância Explicada:\nPC1 = ',pca.explained_variance_ratio_[0], ', PC2 =
 ',pca.explained_variance_ratio_[1])
```

```
Variância Explicada:
PC1 =  0.36951468599607673 , PC2 =  0.18434927059884115
```

In [37]:

```
print("X Original:\n",X_train_std[:2])
print("X Transformado (PC1, PC2):\n",X_train_pca[:2])
```

```
X Original:
 [[ 0.71225893  2.22048673 -0.13025864  0.05962872 -0.50432733 -0.52
831584
  -1.24000033  0.84118003 -1.05215112 -0.29218864 -0.20017028 -0.821
64144
  -0.62946362]
 [ 0.88229214 -0.70457155  1.17533605 -0.09065504  2.34147876  1.016
75879
   0.66299475  1.0887425  -0.49293533  0.13152077  1.33982592  0.549
31269
   1.47568796]]
X Transformado (PC1, PC2):
 [[ 2.38299011  0.45458499]
 [-1.96578183  1.65376939]]
```

In [38]:

```
lr = LogisticRegression()
lr = lr.fit(X_train_pca, y_train)
lr
```

Out[38]:

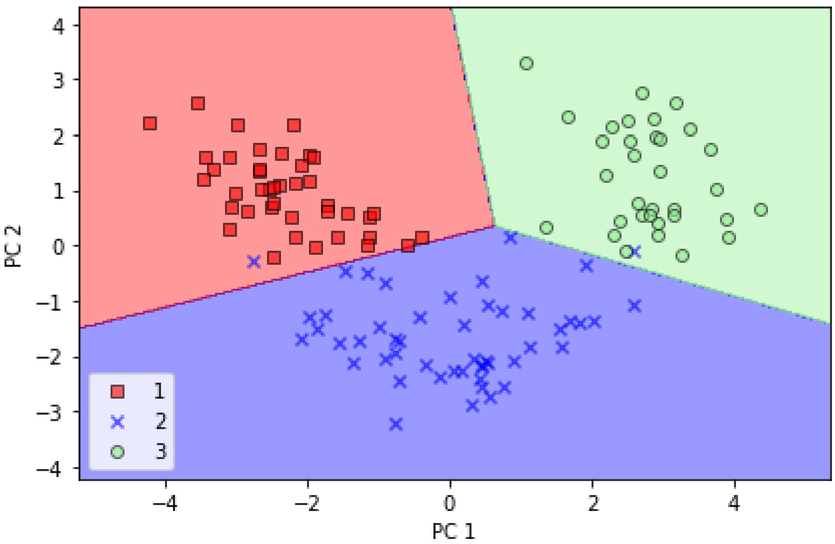
```
LogisticRegression()
```

In [39]:

```
plot_decision_regions(X_train_pca, y_train, classifier=lr)
print('train values')
plt.show()
```

```
*c* argument looks like a single numeric RGB or RGBA sequence, which
should be avoided as value-mapping will have precedence in case its
length matches with *x* & *y*.  Please use the *color* keyword-argum
ent or provide a 2-D array with a single row if you intend to specif
y the same RGB or RGBA value for all points.
*c* argument looks like a single numeric RGB or RGBA sequence, which
should be avoided as value-mapping will have precedence in case its
length matches with *x* & *y*.  Please use the *color* keyword-argum
ent or provide a 2-D array with a single row if you intend to specif
y the same RGB or RGBA value for all points.
*c* argument looks like a single numeric RGB or RGBA sequence, which
should be avoided as value-mapping will have precedence in case its
length matches with *x* & *y*.  Please use the *color* keyword-argum
ent or provide a 2-D array with a single row if you intend to specif
y the same RGB or RGBA value for all points.
```

```
train values
```

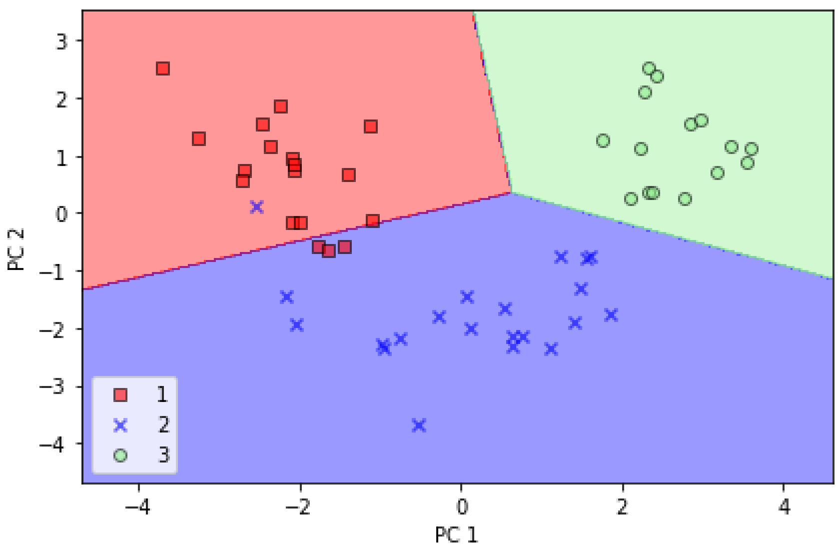


In [40]:

```
plot_decision_regions(X_test_pca, y_test, classifier=lr)
#plt.xlabel('PC 1')
#plt.ylabel('PC 2')
#plt.legend(loc='lower left')
#plt.tight_layout()
# plt.savefig('images/05_05.png', dpi=300)
print('test values')
plt.show()
```

```
*c* argument looks like a single numeric RGB or RGBA sequence, which
should be avoided as value-mapping will have precedence in case its
length matches with *x* & *y*.  Please use the *color* keyword-argum
ent or provide a 2-D array with a single row if you intend to specif
y the same RGB or RGBA value for all points.
*c* argument looks like a single numeric RGB or RGBA sequence, which
should be avoided as value-mapping will have precedence in case its
length matches with *x* & *y*.  Please use the *color* keyword-argum
ent or provide a 2-D array with a single row if you intend to specif
y the same RGB or RGBA value for all points.
*c* argument looks like a single numeric RGB or RGBA sequence, which
should be avoided as value-mapping will have precedence in case its
length matches with *x* & *y*.  Please use the *color* keyword-argum
ent or provide a 2-D array with a single row if you intend to specif
y the same RGB or RGBA value for all points.

test values
```



In [41]:

```
pca = PCA(n_components=None)
X_train_pca = pca.fit_transform(X_train_std)
pca.explained_variance_ratio_
```

Out[41]:

```
array([0.36951469, 0.18434927, 0.11815159, 0.07334252, 0.06422108,
       0.05051724, 0.03954654, 0.02643918, 0.02389319, 0.01629614,
       0.01380021, 0.01172226, 0.00820609])
```

In [42]:

```
pca
```

Out[42]:

```
PCA()
```

In [43]:

```
sum(pca.explained_variance_ratio_)
```

Out[43]:

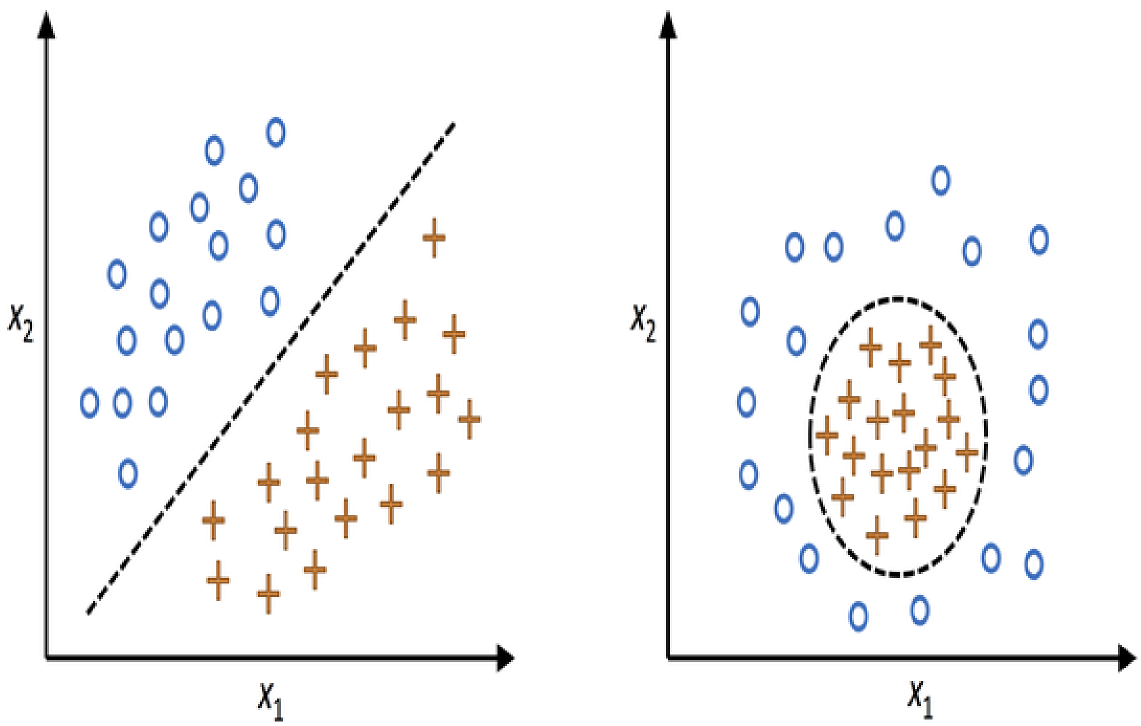
```
1.0
```

Kernel PCA para mapeamento não-linear

In [44]:

```
img = Image.open('image02.png')
width  = 600
height = 400
img = img.resize((width, height), Image.ANTIALIAS)
img
```

Out[44]:



Kernel principal component analysis (KPCA) no scikit-learn

In [45]:

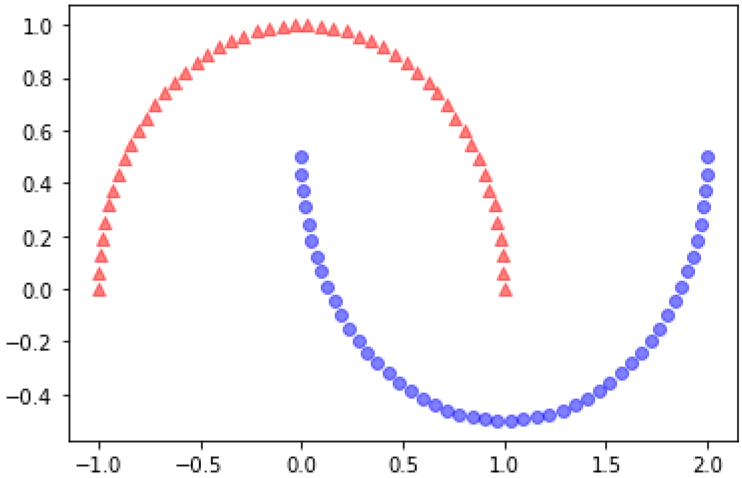
```
from sklearn.datasets import make_moons

X, y = make_moons(n_samples=100, random_state=123)

plt.scatter(X[y == 0, 0], X[y == 0, 1],
            color='red', marker='^', alpha=0.5)
plt.scatter(X[y == 1, 0], X[y == 1, 1],
            color='blue', marker='o', alpha=0.5)
```

Out[45]:

```
<matplotlib.collections.PathCollection at 0x24f7b9578e0>
```



Usando o KPCA para a separação não-linear

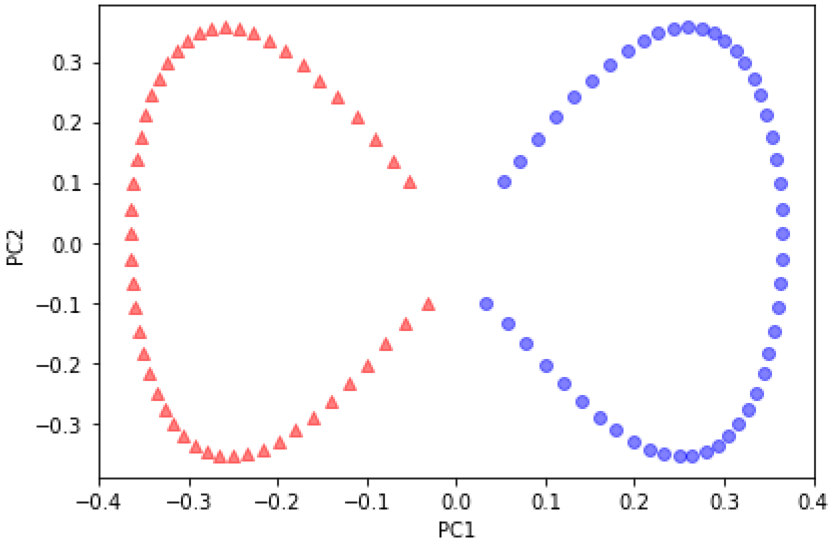
In [46]:

```
from sklearn.decomposition import KernelPCA

X, y = make_moons(n_samples=100, random_state=123)
scikit_kpca = KernelPCA(n_components=2, kernel='rbf', gamma=15)
X_skernpca = scikit_kpca.fit_transform(X)

plt.scatter(X_skernpca[y == 0, 0], X_skernpca[y == 0, 1],
            color='red', marker='^', alpha=0.5)
plt.scatter(X_skernpca[y == 1, 0], X_skernpca[y == 1, 1],
            color='blue', marker='o', alpha=0.5)

plt.xlabel('PC1')
plt.ylabel('PC2')
plt.tight_layout()
# plt.savefig('images/05_19.png', dpi=300)
plt.show()
```



PCA - Consumo de Alimentos no Reino Unido

In [47]:

```
import pandas as pd
```

In [48]:

```
dfUK = pd.read_excel('Food.xlsx')
df = dfUK.copy()
df
```

Out[48]:

	FoodConsumption	England	Wales	Scotland	N_Ireland
0	Cheese	105	103	103	66
1	Carcass meat	245	227	242	267
2	Other meat	685	803	750	586
3	Fish	147	160	122	93
4	Fats and oils	193	235	184	209
5	Sugars	156	175	147	139
6	Fresh potatoes	720	874	566	1033
7	Fresh Veg	253	265	171	143
8	Other Veg	488	570	418	355
9	Processed potatoes	198	203	220	187
10	Processed Veg	360	365	337	334
11	Fresh fruit	1102	1137	957	674
12	Cereals	1472	1582	1462	1494
13	Beverages	57	73	53	47
14	Soft drinks	1374	1256	1572	1506
15	Alcoholic drinks	375	475	458	135
16	Confectionery	54	64	62	41

In [49]:

```
foods = df['FoodConsumption']
foods = foods.values
foods
```

Out[49]:

```
array(['Cheese', 'Carcass meat', 'Other meat', 'Fish', 'Fats and oil
s',
       'Sugars', 'Fresh potatoes', 'Fresh Veg', 'Other Veg',
       'Processed potatoes', 'Processed Veg', 'Fresh fruit', 'Cereal
s',
       'Beverages', 'Soft drinks', 'Alcoholic drinks', 'Confectioner
y'],
      dtype=object)
```

In [50]:

```
len(foods)
```

Out[50]:

```
17
```

In [51]:

```
del df['FoodConsumption']
df
```

Out[51]:

	England	Wales	Scotland	N_Ireland
0	105	103	103	66
1	245	227	242	267
2	685	803	750	586
3	147	160	122	93
4	193	235	184	209
5	156	175	147	139
6	720	874	566	1033
7	253	265	171	143
8	488	570	418	355
9	198	203	220	187
10	360	365	337	334
11	1102	1137	957	674
12	1472	1582	1462	1494
13	57	73	53	47
14	1374	1256	1572	1506
15	375	475	458	135
16	54	64	62	41

In [52]:

```
countries = df.columns
countries
```

Out[52]:

```
Index(['England', 'Wales', 'Scotland', 'N_Ireland'], dtype='object')
```

Obtem a matriz transporta para manipulação dos dados

In [53]:

```
df2 = df.T
df2.columns = foods
df2
```

Out[53]:

	Cheese	Carcass meat	Other meat	Fish	Fats and oils	Sugars	Fresh potatoes	Fresh Veg	Other Veg	Processed potatoes
England	105	245	685	147	193	156	720	253	488	198
Wales	103	227	803	160	235	175	874	265	570	203
Scotland	103	242	750	122	184	147	566	171	418	220
N_Ireland	66	267	586	93	209	139	1033	143	355	187

In [54]:

```
df2.columns
```

Out[54]:

```
Index(['Cheese', 'Carcass meat', 'Other meat', 'Fish', 'Fats and oil
s',
       'Sugars', 'Fresh potatoes', 'Fresh Veg', 'Other Veg',
       'Processed potatoes', 'Processed Veg', 'Fresh fruit', 'Cereal
s',
       'Beverages', 'Soft drinks', 'Alcoholic drinks', 'Confectioner
y'],
      dtype='object')
```

In [55]:

```
data = df2.values
data
```

Out[55]:

```
array([[ 105,  245,  685,  147,  193,  156,  720,  253,  488,  198,
360,
         1102, 1472,   57, 1374,  375,   54],
       [ 103,  227,  803,  160,  235,  175,  874,  265,  570,  203,
365,
         1137, 1582,   73, 1256,  475,   64],
       [ 103,  242,  750,  122,  184,  147,  566,  171,  418,  220,
337,
          957, 1462,   53, 1572,  458,   62],
       [  66,  267,  586,   93,  209,  139, 1033,  143,  355,  187,
334,
          674, 1494,   47, 1506,  135,   41]], dtype=int64)
```

colocar os dados em escala

In [56]:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_std = sc.fit_transform(data.astype(float))
X_std
```

Out[56]:

```
array([[ 0.65827466, -0.01749546, -0.25954622,  0.64458535, -0.63242
919,
         0.13055067, -0.45007561,  0.86331183,  0.37773603, -0.33626
508,
         0.80547723,  0.73740709, -0.64432226, -0.05191741, -0.43523
112,
         0.10499766, -0.13830319],
       [ 0.53580495, -1.27716878,  1.19885635,  1.15244047,  1.53589
947,
         1.54795798,  0.43569619,  1.09352832,  1.40168163,  0.08406
627,
         1.17160324,  0.9292974 ,  1.67946294,  1.60943981, -1.40423
624,
         0.84182336,  0.96812236],
       [ 0.53580495, -0.22744102,  0.54381113, -0.33205912, -1.09707
105,
        -0.54085279, -1.33584741, -0.70983418, -0.49636387,  1.51319
287,
        -0.87870243, -0.0575671 , -0.85557546, -0.46725672,  1.19072
664,
         0.71656299,  0.74683725],
       [-1.72988456,  1.52210526, -1.48312126, -1.4649667 ,  0.19360
077,
        -1.13765587,  1.35022682, -1.24700598, -1.28305378, -1.26099
406,
        -1.09837804, -1.60913739, -0.17956522, -1.09026568,  0.64874
072,
        -1.66338402, -1.57665641]])
```

PCA - Converter 17 dimensões (atributos) em 1 dimensão

In [57]:

```
from sklearn.decomposition import PCA
pca = PCA(1) # somente 1 dimensão
X_std = data
X_pca = pca.fit_transform(X_std)
print('Variância Explicada:\n', pca.explained_variance_ratio_)
```

```
Variância Explicada:
 [0.67444346]
```

In [58]:

```
X_pca
```

Out[58]:

```
array([[-144.99315218],
       [-240.52914764],
       [ -91.869339  ],
       [ 477.39163882]])
```

In [59]:

```
dfpca = pd.DataFrame()
dfpca['PC1'] = X_pca.ravel()
dfpca['Country'] = countries
dfpca
```

Out[59]:

	PC1	Country
0	-144.993152	England
1	-240.529148	Wales
2	-91.869339	Scotland
3	477.391639	N_Ireland

In [60]:

```
dfpca2 = dfpca.sort_values('PC1')
dfpca2 = dfpca2.reset_index(drop=True)
dfpca2
```

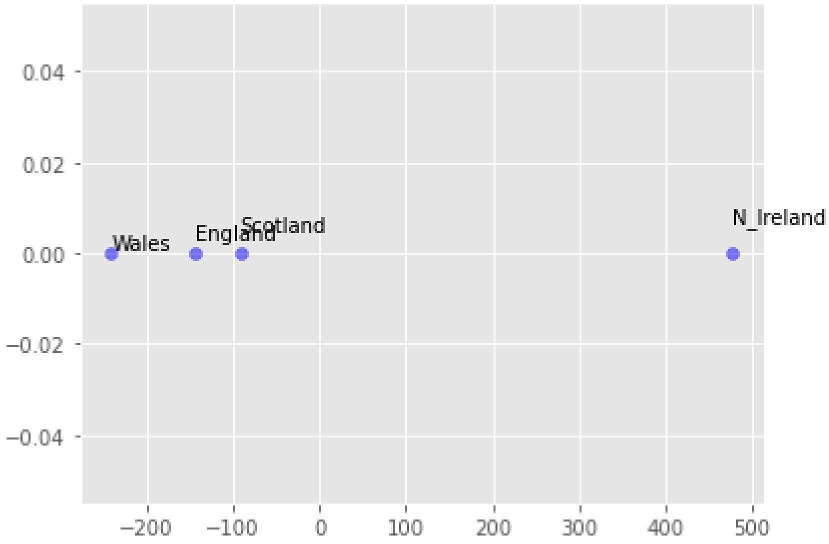
Out[60]:

	PC1	Country
0	-240.529148	Wales
1	-144.993152	England
2	-91.869339	Scotland
3	477.391639	N_Ireland

Plota

In [61]:

```
import matplotlib.pyplot as plt
import numpy as np
plt.style.use('ggplot')
plt.scatter(dfpca2.PC1, np.zeros(len(dfpca)), color='blue', marker='o', alpha=0.
5)
y = 0.001
for i in range(len(dfpca2)):
    country = dfpca2.loc[i,'Country']
    x = dfpca2.loc[i,'PC1']
    plt.annotate(country, (x,y))
    y += 0.002
plt.tight_layout()
plt.show()
```



Analizando o PC1 e o PC2, vemos que A Irlanda do Norte tem um comportamente de outlier (padrão fora da média).
Se olharmos a tabela, perceberemos que a Irlanda do Norte tem um maior consumo de Batatas e consumos mais baixos em frutas, queijo, peixe e bebidas.
Pode ser devido a um fato geográfico: A Irlanda do Norte é o único país do UK, que está fora da Grande Ilha do Reino Unido.

In [62]:

```
dfUK.T
```

Out[62]:

	0	1	2	3	4	5	6	7	8	
FoodConsumption	Cheese	Carcass meat	Other meat	Fish	Fats and oils	Sugars	Fresh potatoes	Fresh Veg	Other Veg	Proce: pota
England	105	245	685	147	193	156	720	253	488	
Wales	103	227	803	160	235	175	874	265	570	
Scotland	103	242	750	122	184	147	566	171	418	
N_Ireland	66	267	586	93	209	139	1033	143	355	

PCA - Converter 17 dimensões (atributos) em 2 dimensões

In [63]:

```
from sklearn.decomposition import PCA
pca = PCA(2) # somente 2 dimensõ
X_std = data
X_pca = pca.fit_transform(X_std)
print(pca.explained_variance_ratio_)
```

```
[0.67444346 0.29052475]
```

In [64]:

```
X_pca
```

Out[64]:

```
array([[-144.99315218,   -2.53299944],
       [-240.52914764, -224.64692488],
       [ -91.869339  ,  286.08178613],
       [ 477.39163882,  -58.90186182]])
```

In [65]:

```
X_pca[:, 0]
```

Out[65]:

```
array([-144.99315218, -240.52914764,  -91.869339  ,  477.39163882])
```

In [66]:

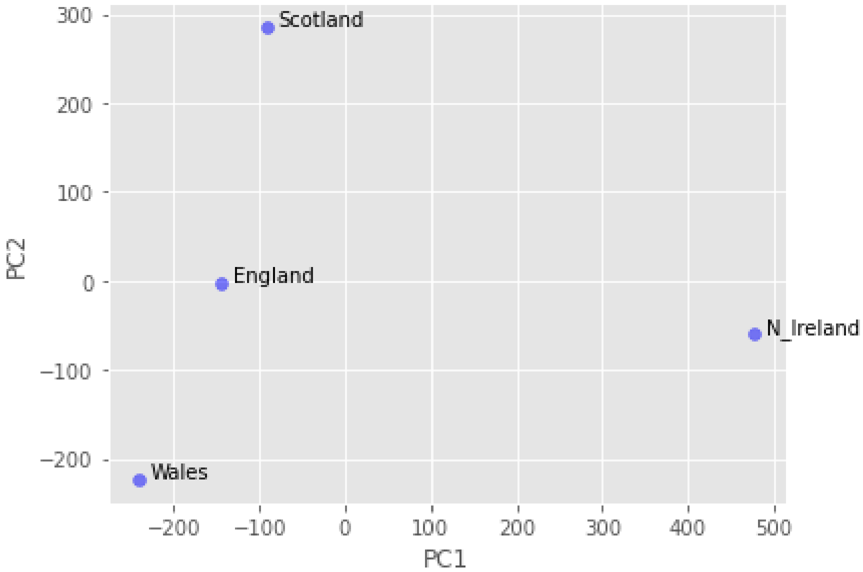
```
dfpca['Country'] = countries
dfpca['PC1'] = X_pca[:, 0]
dfpca['PC2'] = X_pca[:, 1]
dfpca
```

Out[66]:

	PC1	Country	PC2
0	-144.993152	England	-2.532999
1	-240.529148	Wales	-224.646925
2	-91.869339	Scotland	286.081786
3	477.391639	N_Ireland	-58.901862

In [67]:

```
plt.style.use('ggplot')
plt.scatter(dfpca.PC1, dfpca.PC2, color='blue', marker='o', alpha=0.5)
for i in range(len(dfpca2)):
    country = dfpca.loc[i,'Country']
    x = dfpca.loc[i,'PC1'] + 14
    y = dfpca.loc[i,'PC2'] + 2
    plt.annotate(country, (x,y))
plt.tight_layout()
plt.xlabel('PC1')
plt.ylabel('PC2')
plt.show()
```



In [ ]: