eigenfaces-mypca

May 12, 2023

```
M = 5, N^2 = 9
[]: import numpy as np
     X = np.random.randint(10, size=(5, 9))
     print(X)
    [[7 6 7 5 9 3 7 9 4]
     [6 6 3 3 8 1 9 7 3]
     [8 5 2 8 1 1 8 5 5]
     [3 0 6 9 5 1 8 9 2]
     [6 5 9 9 8 8 1 2 8]]
    Matrix form of X
[]: print(X.T)
    [[7 6 8 3 6]
     [6 6 5 0 5]
     [7 3 2 6 9]
     [5 3 8 9 9]
     [9 8 1 5 8]
     [3 1 1 1 8]
     [7 9 8 8 1]
     [9 7 5 9 2]
     [4 3 5 2 8]]
    The Mean array: Mean of Xi in X
[]: phi = np.mean(X, axis = 0)
     print(phi)
    [6. 4.4 5.4 6.8 6.2 2.8 6.6 6.4 4.4]
    New created X matrix with Ai = Xi - phi
[]: A = X - phi
     A = A.T
     print(A)
    [[ 1.
            0.
                  2. -3.
     [ 1.6 1.6 0.6 -4.4 0.6]
```

```
[-1.8 -3.8 1.2 2.2 2.2]
     [ 2.8 1.8 -5.2 -1.2 1.8]
     [ 0.2 -1.8 -1.8 -1.8 5.2]
     [0.4 \ 2.4 \ 1.4 \ 1.4 \ -5.6]
     [ 2.6  0.6 -1.4  2.6 -4.4]
     [-0.4 - 1.4 \ 0.6 - 2.4 \ 3.6]]
    Covaraince Matrix: M x M size since At = M \times N^2 and A = N^2 \times M and Cov = At \times A
[ ]: cov = A.T @ A
    print(cov)
    Γ 13.32 37.32
                    0.12 - 7.48 - 43.28
     [-22.88
              0.12 51.92 -1.68 -27.48]
     [ -8.48 -7.48 -1.68 52.72 -35.08]
     [ -6.28 -43.28 -27.48 -35.08 112.12]]
[]: values1, vectors1 = np.linalg.eig(cov)
    print(values1)
    print()
    print(vectors1)
    [1.47660727e+02 4.53996194e-15 7.69412295e+00 6.68712060e+01
    5.61739441e+01]
    [-0.3228464 -0.4472136 -0.63093265 -0.44767294 0.31190246]
     [-0.2410243 -0.4472136 0.23940211 0.64458993 0.51874631]
     [-0.28974997 -0.4472136 -0.11562837 0.26447449 -0.79544219]
     [ 0.86805195 -0.4472136 -0.19510509 0.09156576 -0.00596088]]
[]: cov_d = A @ A.T
    print(cov_d)
                                        -1.
    [[ 14.
            16.
                  -7.
                       -6.
                             -4.
                                   2.
                                              -8.
                                                     8. 1
     Г 16.
            25.2 -3.8 -16.6 10.6
                                   7.4 - 4.2 - 9.8 10.2
     [ -7.
            -3.8 33.2 11.4 23.6 28.4 -29.2 -6.8 12.2]
     [ -6.
          -16.6 11.4 28.8 -16.8 11.8 -17.4 -12.6
                                                     9.4]
     [ -4.
           10.6 23.6 -16.8 42.8
                                   18.2 -13.6
                                               4.6
                                                     [2.6]
     [ 2.
            7.4 28.4 11.8 18.2 36.8 -38.4 -25.6 24.4]
            -4.2 -29.2 -17.4 -13.6 -38.4 41.2 28.8 -26.2]
     Γ-1.
            -9.8 -6.8 -12.6
     [ -8.
                              4.6 -25.6 28.8 35.2 -24.8]
     Γ8.
            10.2 12.2
                        9.4
                              2.6 24.4 -26.2 -24.8 21.2]]
    5 eigenvectors of Cov d which are At x Ei where Ei are the eigenvectors of Cov
```

[1.6 -2.4 -3.4 0.6 3.6]

```
[]: e1 = A @ vectors1[0]
     # print(e1)
     e2 = A @ vectors1[1]
     # print(e2)
     e3 = A @ vectors1[2]
     # print(e3)
     e4 = A @ vectors1[3]
     # print(e4)
     e5 = A @ vectors1[4]
     # print(e5)
     cov_d_eig = np.array([e1, e2, e3, e4, e5])
     print(cov_d_eig)
    -0.7062798 -2.59802684 2.27504282]
     [-0.24169288 \quad 0.54624682 \quad 3.55617448 \quad 1.22472095 \quad 2.67052733 \quad 4.30379802
      -4.45915276 -2.76074352 2.57394189]
     [-1.69598986 -3.48248726 2.12794725 4.97987767 -2.56450805 1.86307477
      -2.83711285 -1.83670425 1.18662092]
     [-1.31443018 -2.88947181 -1.70205807 0.91407865 -2.76418223 -3.65718794]
       3.47364822 3.32778093 -2.82570866]
     [ 0.20314448 \ 0.14981243 \ 3.15903332 \ 0.09112278 \ 2.51949894 \ 1.13396906 ]
      -0.83766596 2.5260529 -0.07940181]]
    EigenValues of Cov and Cov d
[]: print(values1)
    [1.47660727e+02 4.53996194e-15 7.69412295e+00 6.68712060e+01
     5.61739441e+01]
    Let's select the Top k highest EigValues and corresponding EigVectors of Cov_d
[ ]: k = 3
     indices = np.argsort(values1)[-3 : ][::-1]
     print(f"The indices of the top {k} Eigenvalues are:")
     print(indices)
     print(f"\nThe corresponding top {k} Eigenvectors of Cov_d are:")
     print(cov_d_eig[indices])
    The indices of the top 3 Eigenvalues are:
    [0 3 4]
    The corresponding top 3 Eigenvectors of Cov_d are:
     \hbox{\tt [[ 3.04896844 \ 2.09819107 \ -1.77453384 \ 1.28725827 \ -3.88625835 \ 0.38126846 } 
      -0.7062798 -2.59802684 2.27504282
     [-1.31443018 -2.88947181 -1.70205807 0.91407865 -2.76418223 -3.65718794]
       3.47364822 3.32778093 -2.82570866]
     [ \ 0.20314448 \ \ 0.14981243 \ \ 3.15903332 \ \ 0.09112278 \ \ 2.51949894 \ \ 1.13396906
```

```
-0.83766596 2.5260529 -0.07940181]]
```

These top K Eigenvectors are called EIGENFACES

Now we want to represent each Ai which is Xi - phi as the linear combination of each of the Top k eigenvectors as Ai = Xi - $phi = (wi, 1 \times E1) + (wi, 2 \times E2) + + (wi, k \times Ek)$

0.0.1 Let's see PCA

```
[]: from sklearn.decomposition import PCA
     from sklearn.datasets import load_wine
     from sklearn.preprocessing import StandardScaler
     wine = load wine()
     X, target = wine.data, wine.target
     print(X.shape)
     print(X)
    (178, 13)
    [[1.423e+01 1.710e+00 2.430e+00 ... 1.040e+00 3.920e+00 1.065e+03]
     [1.320e+01 1.780e+00 2.140e+00 ... 1.050e+00 3.400e+00 1.050e+03]
     [1.316e+01 2.360e+00 2.670e+00 ... 1.030e+00 3.170e+00 1.185e+03]
     [1.327e+01 4.280e+00 2.260e+00 ... 5.900e-01 1.560e+00 8.350e+02]
     [1.317e+01 2.590e+00 2.370e+00 ... 6.000e-01 1.620e+00 8.400e+02]
     [1.413e+01 4.100e+00 2.740e+00 ... 6.100e-01 1.600e+00 5.600e+02]]
```

0.0.2 Scaling using StandardScaler

```
[]: scaler = StandardScaler()
   scaler.fit(X)
   X_scaled = scaler.transform(X)
   print(X_scaled)
   [[ 1.51861254 -0.5622498
                     0.23205254 ... 0.36217728 1.84791957
     1.01300893]
   [ 0.24628963 -0.49941338 -0.82799632 ... 0.40605066 1.1134493
    0.96524152]
   1.39514818]
   [ 0.33275817 \ 1.74474449 \ -0.38935541 \ ... \ -1.61212515 \ -1.48544548
    0.28057537]
   0.29649784]
   -0.59516041]]
```

0.0.3 Standard Scaler working: replace each Xi in X with (Xi - mean)/(std), where mean = sum(Xi)/N (it is itself an array like Xi) and std = root(sum(Xi - mean)/N)

```
[]: means = np.mean(X, axis = 0)
    stds = np.std(X, axis = 0)
    My_X_scaled = (X - means)/stds
    print(My_X_scaled)
    [[ 1.51861254 -0.5622498
                             0.23205254 ... 0.36217728 1.84791957
      1.01300893]
     [ 0.24628963 -0.49941338 -0.82799632 ... 0.40605066 1.1134493
      0.965241527
     1.395148187
     [ 0.33275817 \ 1.74474449 \ -0.38935541 \ ... \ -1.61212515 \ -1.48544548 
      0.28057537]
     0.29649784]
     -0.59516041]]
    0.0.4 Covariance Matrix Cov = (A \times At)/(M - 1)
[]: cov = np.cov(My X scaled.T)
    print(cov)
    print()
    Mycov = (My_X_scaled.T @ My_X_scaled)/(My_X_scaled.shape[0] - 1)
    print(Mycov)
    [[ 1.00564972  0.09493026  0.21273976  -0.31198788  0.27232816  0.29073446
      0.23815287 -0.15681042 0.13747022 0.549451
                                                   -0.07215255 0.07275191
      0.64735687]
      \begin{smallmatrix} 0.09493026 & 1.00564972 & 0.16497228 & 0.29013035 & -0.05488343 & -0.3370606 \end{smallmatrix} 
     -0.41332866 \quad 0.29463237 \ -0.22199334 \quad 0.25039204 \ -0.56446685 \ -0.37079354
     -0.19309537]
     [ \ 0.21273976 \ \ 0.16497228 \ \ 1.00564972 \ \ 0.44587209 \ \ 0.28820583 \ \ 0.12970824
      0.11572743 0.1872826
                             0.00970647 0.2603499 -0.07508874 0.00393333
      0.22488969]
     [-0.31198788 0.29013035 0.44587209 1.00564972 -0.0838039 -0.32292752
     -0.353355
                  0.36396647 \ -0.19844168 \ \ 0.01883781 \ -0.27550299 \ -0.27833221
     -0.443086187
     [ 0.27232816 -0.05488343  0.28820583 -0.0838039
                                                    1.00564972 0.21561254
      0.19688989 -0.25774204 0.23777643 0.20107967 0.05571118 0.06637684
      0.39557317]
     [ 0.29073446 -0.3370606
                             0.12970824 -0.32292752 0.21561254 1.00564972
      0.86944804 -0.45247731 0.61587304 -0.05544792 0.43613151 0.70390388
```

```
0.500929091
 [ 0.23815287 -0.41332866  0.11572743 -0.353355  0.19688989  0.86944804
  1.00564972 -0.54093859 0.65637929 -0.17335329 0.54654907 0.79164133
  0.496985187
 [-0.15681042 0.29463237 0.1872826 0.36396647 -0.25774204 -0.45247731
 -0.54093859 \quad 1.00564972 \quad -0.36791202 \quad 0.13984265 \quad -0.26412347 \quad -0.50611293
 -0.31314443]
 [ 0.13747022 -0.22199334  0.00970647 -0.19844168  0.23777643  0.61587304
  0.65637929 -0.36791202 1.00564972 -0.02539259 0.29721399 0.52199968
  0.332283461
               0.25039204 \quad 0.2603499 \quad 0.01883781 \quad 0.20107967 \quad -0.05544792
 [ 0.549451
 -0.17335329 0.13984265 -0.02539259 1.00564972 -0.52476129 -0.43123763
  0.31788599]
 [-0.07215255 -0.56446685 -0.07508874 -0.27550299 0.05571118 0.43613151
  0.54654907 - 0.26412347 \quad 0.29721399 - 0.52476129 \quad 1.00564972 \quad 0.56866303
  0.23751782]
  \begin{smallmatrix} 0.07275191 & -0.37079354 & 0.00393333 & -0.27833221 & 0.06637684 & 0.70390388 \end{smallmatrix} 
  0.79164133 -0.50611293 0.52199968 -0.43123763 0.56866303 1.00564972
  0.31452809]
[ 0.64735687 -0.19309537  0.22488969 -0.44308618  0.39557317  0.50092909
  0.49698518 - 0.31314443 \ 0.33228346 \ 0.31788599 \ 0.23751782 \ 0.31452809
  1.00564972]]
0.23815287 - 0.15681042 \ 0.13747022 \ 0.549451 \ -0.07215255 \ 0.07275191
  0.64735687]
 [0.09493026 \ 1.00564972 \ 0.16497228 \ 0.29013035 \ -0.05488343 \ -0.3370606]
 -0.41332866 0.29463237 -0.22199334 0.25039204 -0.56446685 -0.37079354
 -0.19309537]
 [ 0.21273976 \ 0.16497228 \ 1.00564972 \ 0.44587209 \ 0.28820583 \ 0.12970824 ]
  0.11572743 0.1872826
                           0.00970647 0.2603499 -0.07508874 0.00393333
  0.22488969]
 \begin{bmatrix} -0.31198788 & 0.29013035 & 0.44587209 & 1.00564972 & -0.0838039 & -0.32292752 \end{bmatrix}
 -0.353355
            0.36396647 -0.19844168 0.01883781 -0.27550299 -0.27833221
 -0.44308618]
 [ 0.27232816 -0.05488343  0.28820583 -0.0838039  1.00564972  0.21561254
  0.19688989 -0.25774204 0.23777643 0.20107967 0.05571118 0.06637684
  0.39557317
 0.86944804 - 0.45247731 \ 0.61587304 - 0.05544792 \ 0.43613151 \ 0.70390388
  0.50092909]
 [ 0.23815287 -0.41332866  0.11572743 -0.353355  0.19688989  0.86944804
  1.00564972 -0.54093859 0.65637929 -0.17335329 0.54654907 0.79164133
  0.49698518]
 \begin{bmatrix} -0.15681042 & 0.29463237 & 0.1872826 & 0.36396647 & -0.25774204 & -0.45247731 \end{bmatrix}
 -0.54093859 1.00564972 -0.36791202 0.13984265 -0.26412347 -0.50611293
 -0.313144431
 [0.13747022 - 0.22199334 \ 0.00970647 - 0.19844168 \ 0.23777643 \ 0.61587304
```

```
0.65637929 -0.36791202 1.00564972 -0.02539259 0.29721399 0.52199968
 0.33228346]
[ 0.549451
             0.25039204 0.2603499
                                     0.01883781 0.20107967 -0.05544792
-0.17335329 0.13984265 -0.02539259 1.00564972 -0.52476129 -0.43123763
 0.317885997
[-0.07215255 -0.56446685 -0.07508874 -0.27550299 0.05571118 0.43613151
 0.54654907 - 0.26412347 \ 0.29721399 - 0.52476129 \ 1.00564972 \ 0.56866303
 0.23751782]
[ 0.07275191 -0.37079354  0.00393333 -0.27833221  0.06637684  0.70390388
 0.79164133 -0.50611293 0.52199968 -0.43123763 0.56866303 1.00564972
 0.31452809]
[ 0.64735687 -0.19309537  0.22488969 -0.44308618  0.39557317  0.50092909
 0.49698518 - 0.31314443 \ 0.33228346 \ 0.31788599 \ 0.23751782 \ 0.31452809
 1.00564972]]
```

0.0.5 EigenValues and EigenVectors

```
[]: values, vectors = np.linalg.eig(cov)
print(values)
print()
max_abs_idx = np.argmax(np.abs(vectors), axis=0)
signs = np.sign(vectors[max_abs_idx, range(vectors.shape[0])])
vectors = vectors*signs[np.newaxis,:]
vectors = vectors.T
print(vectors)
```

```
[4.73243698 2.51108093 1.45424187 0.92416587 0.85804868 0.64528221
0.55414147 0.10396199 0.35046627 0.16972374 0.29051203 0.22706428
0.25232001]
 \begin{bmatrix} 0.1443294 & -0.24518758 & -0.00205106 & -0.23932041 & 0.14199204 & 0.39466085 \end{bmatrix} 
  0.4229343 -0.2985331
                           0.31342949 -0.0886167
                                                    0.29671456 0.37616741
  0.28675223]
0.48365155 0.22493093 0.31606881 -0.0105905
                                                    0.299634
                                                                0.06503951
 -0.00335981 0.02877949 0.03930172 0.52999567 -0.27923515 -0.16449619
  0.364902831
[-0.20738262 0.08901289 0.6262239
                                       0.61208035 0.13075693 0.14617896
  -0.12674592]
 [-0.0178563
               0.53689028 -0.21417556 0.06085941 -0.35179658 0.19806835
  0.15229479 -0.20330102 0.39905653 0.06592568 -0.42777141 0.18412074
 -0.23207086]
\begin{bmatrix} -0.26566365 & 0.03521363 & -0.14302547 & 0.06610294 & 0.72704851 & -0.14931841 \end{bmatrix}
 -0.10902584 -0.50070298 0.13685982 -0.07643678 -0.17361452 -0.10116099
 -0.1578688 ]
  \begin{smallmatrix} 0.21353865 & 0.53681385 & 0.15447466 & -0.10082451 & 0.03814394 & -0.0841223 \end{smallmatrix} 
 -0.01892002 -0.25859401 -0.53379539 -0.41864414 0.10598274 0.26585107
  0.11972557]
```

```
[-0.05639636 \quad 0.42052391 \quad -0.14917061 \quad -0.28696914 \quad 0.3228833 \quad -0.02792498
      -0.06068521 0.59544729 0.37213935 -0.22771214 0.23207564 -0.0447637
       0.0768045 ]
      \begin{bmatrix} 0.01496997 & 0.02596375 & -0.14121803 & 0.09168285 & 0.05677422 & -0.46390791 \end{bmatrix} 
       0.83225706 0.11403985 -0.11691707 -0.0119928 -0.08988884 -0.15671813
       0.014447347
     [ \ 0.39613926 \ \ 0.06582674 \ -0.17026002 \ \ 0.42797018 \ -0.15636143 \ -0.40593409 ]
      -0.18724536 -0.23328465 0.36822675 -0.03379692 0.43662362 -0.07810789
       0.12002267]
      \begin{bmatrix} -0.26628645 & 0.12169604 & -0.04962237 & -0.05574287 & 0.06222011 & -0.30388245 \end{bmatrix} 
      0.60095872
      -0.07940162]
      \begin{bmatrix} -0.50861912 & 0.07528304 & 0.30769445 & -0.20044931 & -0.27140257 & -0.28603452 \end{bmatrix} 
      -0.04957849 -0.19550132 0.20914487 -0.05621752 -0.08582839 -0.1372269
       0.57578611]
     \lceil -0.22591696 \quad 0.07648554 \quad -0.49869142 \quad 0.47931378 \quad 0.07128891 \quad 0.30434119 
      -0.02569409 0.11689586 -0.23736257 0.0318388 -0.04821201 0.0464233
       0.53926983]
     [ 0.21160473 -0.30907994 -0.02712539  0.05279942  0.06787022 -0.32013135
      -0.16315051 0.21553507 0.1341839 -0.29077518 -0.52239889 0.52370587
       0.162116 ]]
[]: indices = np.argsort(values)[::-1]
    eig = vectors[indices]
    print(eig)
    [[0.1443294 -0.24518758 -0.00205106 -0.23932041 0.14199204 0.39466085]
       0.4229343 - 0.2985331 0.31342949 - 0.0886167 0.29671456 0.37616741
       0.286752231
     [ 0.48365155  0.22493093  0.31606881 -0.0105905
                                                       0.299634
                                                                   0.06503951
      -0.00335981 0.02877949 0.03930172 0.52999567 -0.27923515 -0.16449619
       0.36490283]
     [-0.20738262 0.08901289 0.6262239
                                           0.61208035 0.13075693 0.14617896
       -0.12674592]
     [-0.0178563
                   0.15229479 -0.20330102 0.39905653 0.06592568 -0.42777141 0.18412074
      -0.232070861
     [-0.26566365 \quad 0.03521363 \quad -0.14302547 \quad 0.06610294 \quad 0.72704851 \quad -0.14931841
      -0.10902584 -0.50070298 0.13685982 -0.07643678 -0.17361452 -0.10116099
      -0.1578688 ]
     -0.01892002 -0.25859401 -0.53379539 -0.41864414 0.10598274 0.26585107
       0.11972557]
     \lceil -0.05639636 \quad 0.42052391 \quad -0.14917061 \quad -0.28696914 \quad 0.3228833 \quad -0.02792498 
      -0.06068521 0.59544729 0.37213935 -0.22771214 0.23207564 -0.0447637
       0.0768045 ]
      \begin{smallmatrix} 0.39613926 & 0.06582674 & -0.17026002 & 0.42797018 & -0.15636143 & -0.40593409 \end{smallmatrix}
```

```
-0.18724536 -0.23328465 0.36822675 -0.03379692 0.43662362 -0.07810789
 0.12002267]
[-0.50861912 \quad 0.07528304 \quad 0.30769445 \quad -0.20044931 \quad -0.27140257 \quad -0.28603452
-0.04957849 -0.19550132 0.20914487 -0.05621752 -0.08582839 -0.1372269
 0.57578611]
[ 0.21160473 -0.30907994 -0.02712539  0.05279942  0.06787022 -0.32013135
-0.16315051 0.21553507 0.1341839 -0.29077518 -0.52239889 0.52370587
 0.162116 ]
 \begin{bmatrix} -0.22591696 & 0.07648554 & -0.49869142 & 0.47931378 & 0.07128891 & 0.30434119 \end{bmatrix} 
-0.02569409 0.11689586 -0.23736257 0.0318388 -0.04821201 0.0464233
 0.53926983]
[-0.26628645 \quad 0.12169604 \quad -0.04962237 \quad -0.05574287 \quad 0.06222011 \quad -0.30388245
-0.04289883 0.04235219 -0.09555303 0.60422163 0.259214
                                                                 0.60095872
-0.07940162]
 \begin{bmatrix} 0.01496997 & 0.02596375 & -0.14121803 & 0.09168285 & 0.05677422 & -0.46390791 \end{bmatrix} 
 0.01444734]]
```

0.0.6 Select the top K eigenvectors and Final Projection

```
[]: k = 2
W = eig[:k]
X_proj = My_X_scaled @ W.T
print(X_proj.shape)
print(X_proj[:10])

(178, 2)
[[ 3.31675081   1.44346263]
       [ 2.20946492 -0.33339289]
```

[3.05025392 2.12240111] [2.44908967 1.17485013]

[2.05943687 1.60896307]

[2.75362819 0.78943767]]

0.0.7 Built-in PCA

```
[]: model = PCA(n_components = k)
X_2D = model.fit_transform(X_scaled)
print(X_2D[:10])
```

[[3.31675081 -1.44346263]

[2.20946492 0.33339289]

[2.51674015 -1.0311513]

[3.75706561 -2.75637191]

```
[ 1.00890849 -0.86983082]
[ 3.05025392 -2.12240111]
[ 2.44908967 -1.17485013]
[ 2.05943687 -1.60896307]
[ 2.5108743 -0.91807096]
[ 2.75362819 -0.78943767]]
```

1 YES !!!! SAME RESULT FROM BUILT-IN AND MY OWN PCA!!