

```
In [1]: import numpy as np
import matplotlib.pyplot as plt
```

## Generating the Symmetric Matrices

To generate symmetric matrix from any general matrix M, we can do any one of the following

$M_{\text{symm}} = (M+M.T)/2$

$M_{\text{symm}} = M^*M.T$

Using rules of matrix transpose, it can be shown that these two matrices are symmetric for any matrix M

```
In [2]: N = 10
A = np.random.rand(N,N)
A_Symm = (A + A.T)/2
A_Symm*=2
A_Symm-=1
print(A_Symm)

[[ 0. 51362694  0.02375238 -0.57354865 -0.52947567 -0.56655558 -0.0010004
 3 0.21929146 -0.1587675  0.64460971 -0.22849717]
 1 0.02375238  0.85687269  0.86637343 -0.6393855  0.50356679 -0.5671016
 0 -0.28202469  0.25638067  0.74370076  0.39420788]
 3 [-0.57354865  0.86637343 -0.20362728  0.41619781 -0.0674289  0.7366903
 0 -0.6785701  0.14691901  0.02618289  0.10853407]
 3 [-0.52947567 -0.6393855  0.41619781 -0.61600671 -0.12818749  0.0486808
 0 -0.57794609  0.33673342 -0.06714558  0.05619415]
 6 [-0.56655558  0.50356679 -0.0674289  0.12818749 -0.58481996  0.1593887
 0 -0.3046379  0.39828063  0.80487648 -0.69462498]
 8 [-0.00100043 -0.56710161  0.73669033  0.04868083  0.15938876  0.9906803
 0 0.14516898 -0.08241913  0.26028619  0.51602895]
 8 [-0.21929146 -0.28202469 -0.6785701 -0.57794609 -0.3046379  0.1451689
 0 -0.61249417 -0.1417148  0.81758531 -0.17464582]
 3 [-0.1587675  0.25638067  0.14691901  0.33673342  0.39828063 -0.0824191
 0 -0.1417148  0.89679732 -0.2961392 -0.0670925 ]
 9 [ 0.64460971  0.74370076  0.02618289 -0.06714558  0.80487648  0.2602861
 0 0.81758531 -0.2961392  0.6153814 -0.23107845]
 5 [-0.22849717  0.39420788  0.10853407  0.05619415 -0.69462498  0.5160289
 0 -0.17464582 -0.0670925 -0.23107845  0.14642859]]
```

```
In [3]: plt.imshow(A_Symm)
plt.colorbar()
plt.savefig("Original Matrix")
plt.show()
```

## Eigenvectors and Eigenvalues

There are two standard methods to compute the eigenvectors and eigenvalues, one for any general matrices, the second one is specifically for real symmetric matrices. Since this is a symmetric matrix, the eigenvalues are all always real, the set of eigenvectors are orthogonal, and hence represent the "dimensions" or "degrees of freedom" in which the data exists.

```
In [4]: W, V = np.linalg.eig(A_Symm)
print("The eigenvalues are \n")
print(W)
print("The eigenvectors are \n")
print(V)

The eigenvalues are

[ 2.17746757  2.02819928  1.5618529 -2.14835398  0.9576927  0.54601796
 -1.73757565 -0.10570437 -0.88034648 -0.39641073]
The eigenvectors are

[[-0.405990252 -0.32845758  0.04840936  0.28806855 -0.08100624  0.5476180
 5 -0.00276859 -0.54917049 -0.16996785 -0.07140934]
 [-0.40134277  0.62980716 -0.09682022 -0.05486476 -0.37679816  0.0843203
 9 -0.49936468 -0.00916899  0.03708314  0.17312288]
 [ 0.1448123  0.45279265  0.24728691  0.30873667 -0.1055309 -0.0894596
 6 0.45153661 -0.40563666  0.47253523 -0.0817515 ]
 [ 0.29327398  0.07109931  0.01274624  0.2316118  0.16632393 -0.1054714
 4 -0.55627518 -0.16478143 -0.02845117 -0.69205233]
 [-0.16921227  0.26857131 -0.02574508  0.56672736  0.38956908 -0.2793262
 8 0.10563638  0.06342577 -0.53947778  0.20344179]
 [ 0.16620644  0.04174608  0.83356909 -0.14882385  0.22997872  0.1479000
 7 -0.27297487 -0.05236924 -0.08134798  0.30823168]
 [-0.26138429 -0.24660095  0.09901254  0.49551921  0.1267833  0.0604635
 8 -0.19828155  0.46213957  0.58032281  0.0782974 ]
 [ 0.16403861  0.35528614 -0.2782386 -0.10408752  0.53109801  0.6622390
 6 0.09112728  0.14084193  0.09758868 -0.01802605]
 [-0.62152251  0.11240367  0.28014482 -0.33982411  0.25601971 -0.1235677
 6 0.23392453  0.14087289  0.00256769 -0.50172314]
 [ 0.17149017  0.10878474  0.25645697  0.2232972 -0.49428862  0.3413125
 7 0.22200248  0.49660216 -0.31887032 -0.29108861]]
```

```
In [5]: ## Get the dimensions of the matrices

print("A_Symm ", A_Symm.shape)
print("Eigenvectors ", V.shape)
print("Eigenvalues ", W.shape)

A_Symm (10, 10)
Eigenvectors (10, 10)
Eigenvalues (10,)
```

```
In [6]: W, v = np.linalg.eigh(A_Symm)
print("The eigenvalues are \n")
print(w)
print("The eigenvectors are \n")
print(v)

The eigenvalues are

[-2.14835398 -1.73757565 -0.88034648 -0.39641073 -0.10570437  0.54601796
 0.9576927  1.5618529  2.02819928  2.17746757]
The eigenvectors are

[[ 0.28806855  0.00276859  0.16996785  0.07140934  0.54917049 -0.5476180
 5 0.08100624  0.04840936  0.32845758 -0.405990252]
 [-0.05486476  0.49936468 -0.03708314 -0.17312288  0.00916899 -0.0843203
 9 0.37679816 -0.09682022 -0.62980716 -0.40134277]
 [ 0.30873667 -0.45153661 -0.47253523  0.0817515  0.40563666  0.0894596
 6 0.1055309  0.24728691 -0.45279265  0.1448123 ]
 [ 0.2316118  0.55627518  0.02845117  0.69205233  0.16478143  0.1054714
 4 -0.16632393  0.01274624 -0.07109931  0.29327398]
 [ 0.56672736 -0.10563638  0.53947778 -0.20344179 -0.06342577  0.2793262
 8 -0.38956908 -0.02574508 -0.26857131 -0.16921227]
 [-0.14882385  0.27297487  0.05134798  0.30823168  0.05236924 -0.1479000
 7 -0.22997872  0.83356909 -0.04174608  0.16620644]
 [ 0.49551921  0.19828155 -0.58032281 -0.0782974 -0.46213957  0.0604635
 8 -0.1267833  0.09901254  0.24660095 -0.26138429]
 [-0.10408752 -0.09112728 -0.09758868  0.01802605 -0.14084193  0.6622390
 6 -0.53109801 -0.27823386 -0.35528614  0.16403861]
 [-0.33982411 -0.23392453 -0.00256769  0.50172314 -0.14087289  0.1235677
 6 -0.25601971  0.28014482 -0.11240367 -0.62152251]
 [ 0.2232972 -0.22200248  0.31887032  0.29108861 -0.49660216 -0.3413125
 7 0.49428862  0.25645697 -0.10878474  0.17149017]]
```

## Generating Approximation to the matrices

There are many methods to generate approximations to the matrices. We work with the following three methods and configurations

1. Eigenvalue Decomposition (2 eigenvectors)
2. Eigenvalue Decomposition (4 eigenvectors)

```
In [7]: ## Before moving ahead, first we reconstruct the matrix
## The entire matrix through the entire set of eigenvalues and eigenvectors

Lambda = np.diag(W)
A_recon = V @ Lambda @ np.linalg.inv(V)
print(A_recon)

[[ 0. 51362694  0.02375238 -0.57354865 -0.52947567 -0.56655558 -0.0010004
 3 0.21929146 -0.1587675  0.64460971 -0.22849717]
 1 0.02375238  0.85687269  0.86637343 -0.6393855  0.50356679 -0.5671016
 0 -0.28202469  0.25638067  0.74370076  0.39420788]
 3 [-0.57354865  0.86637343 -0.20362728  0.41619781 -0.0674289  0.7366903
 0 -0.6785701  0.14691901  0.02618289  0.10853407]
 3 [-0.52947567 -0.6393855  0.41619781 -0.61600671 -0.12818749  0.0486808
 0 -0.57794609  0.33673342 -0.06714558  0.05619415]
 6 [-0.56655558  0.50356679 -0.0674289 -0.12818749 -0.58481996  0.1593887
 0 -0.3046379  0.39828063  0.80487648 -0.69462498]
 8 [-0.00100043 -0.56710161  0.73669033  0.04868083  0.15938876  0.9906803
 0 0.14516898 -0.08241913  0.26028619  0.51602895]
 8 [-0.21929146 -0.28202469 -0.6785701 -0.57794609 -0.3046379  0.1451689
 0 -0.61249417 -0.1417148  0.81758531 -0.17464582]
 3 [-0.1587675  0.25638067  0.14691901  0.33673342  0.39828063 -0.0824191
 0 -0.1417148  0.89679732 -0.2961392 -0.0670925 ]
 9 [ 0.64460971  0.74370076  0.02618289 -0.06714558  0.80487648  0.2602861
 0 0.81758531 -0.2961392  0.6153814 -0.23107845]
 5 [-0.22849717  0.39420788  0.10853407  0.05619415 -0.69462498  0.5160289
 0 -0.17464582 -0.0670925 -0.23107845  0.14642859]]
```

```
In [8]: plt.imshow(A_recon)
plt.colorbar()
plt.savefig("Reconstructed Matrix")
plt.show()
```

```
In [9]: ## Generating the matrix of the top 2 eigenvalues and the matrices containing the eigenvectors
E_2 = np.zeros((2,2))
np.fill_diagonal(E_2, [W[0], W[1]])

Q_2 = V[:,0:2]
A_2 = np.dot(np.dot(Q_2, E_2), Q_2.T)
print(A_2)

[[ 0.57756374 -0.06484069 -0.42963109 -0.30657191 -0.02935964 -0.1747101
 3 0.39530177 -0.38166742  0.4744454 -0.22403974]
 [-0.06484069  1.15523737  0.45183271 -0.16547488  0.49094257 -0.0919242
 4 -0.08657518  0.31047832  0.68673685 -0.01090828]
 [-0.42963109  0.45183271  0.46148662  0.15777067  0.19328676  0.0907465
 7 -0.30888766  0.37800368 -0.09275469  0.15397786]
 [-0.30657191  0.16547488  0.15777067  0.19753595 -0.0693291  0.1121584
 7 -0.20247933  0.4599877 -0.3806919  0.12519984]
 [-0.02935964  0.49094257  0.19328676  0.0693291  0.20864211 -0.0384997
 0 -0.03801937  0.13308938  0.29023069 -0.00392947]
 [-0.17471013 -0.09192424  0.09074657  0.11215847 -0.0384997  0.0636862
 5 -0.11547691  0.08944893 -0.21541753  0.0712746 ]
 [ 0.39530177 -0.08657518 -0.30888766 -0.20247933 -0.03801937 -0.1154769
 1 0.2721073 -0.27106198  0.29752379 -0.15201395]
 [-0.38166742  0.31047832  0.37800368  0.1559877  0.13308938  0.0894489
 3 -0.27106198  0.31460878 -0.14100376  0.13964368]
 [ 0.4744454  0.68673685 -0.09275469 -0.3806919  0.29023069 -0.2154175
 3 0.29752379 -0.14100376  0.8667599 -0.20728496]
 [-0.22403974 -0.01090828  0.15397786  0.12519984 -0.00392947  0.0712746
 0 -0.15201395  0.13964368 -0.20728496  0.08003803]]
```

```
In [10]: plt.imshow(A_2)
plt.colorbar()
plt.savefig("2-Rank Approximation")
plt.show()
```

```
In [11]: ## Generating the matrix of the top 2 eigenvalues and the matrices containing the eigenvectors
E_4 = np.zeros((4,4))
np.fill_diagonal(E_4, [W[0], W[1], W[2], W[3]])

Q_4 = V[:,0:4]
A_4 = np.dot(np.dot(Q_4, E_4), Q_4.T)
print(A_4)

[[ 0.40294598 -0.03820677 -0.602003 -0.44894653 -0.38203857 -0.0195822
 9 0.09612437 -0.33828723  0.70593472 -0.34284212]
 [-0.03820677  1.16341157  0.45082871 -0.14010251  0.56163526 -0.2355173
 9 -0.04314143  0.34028386  0.60431894 -0.02336962]
 [-0.602003  0.45082871  0.35221768  0.09097113 -0.19255312  0.5114036
 8 -0.5993123  0.33958131  0.24084153  0.10492055]
 [-0.44894653 -0.14010251  0.09097113  0.00907113  0.08254335 -0.35183616  0.2028053
 4 -0.4470707  0.20224099 -0.20602376  0.01919618]
 [-0.38203857  0.56163526 -0.19255312 -0.35183616 -0.4803308  0.1091801
 1 -0.64531066  0.27100695  0.69271244 -0.28611288]
 [-0.01958229  0.2355173  0.51140368  0.20280534  0.10918011  1.1013372
 0 0.17185925 -0.30606668  0.04065575  0.47655307]
 [ 0.09612437 -0.04314143 -0.5993123 -0.4470707 -0.64531066  0.1718592
 5 -0.24080641 -0.20328246  0.70260621 -0.3506586]
 [-0.33828723  0.34028386  0.33958131  0.20224099  0.27100695 -0.3060666
 8 -0.20328246  0.41224246 -0.33873399  0.07813066]
 [ 0.70593472  0.60431894  0.24084153 -0.20602376  0.69271244  0.0406557
 5 0.70260621 -0.33873399  0.74124303  0.06197418]
 [-0.34284212 -0.02336962  0.10492055  0.01919618 -0.28611288  0.4765530
 7 -0.3506586  0.07813066  0.06794742  0.08364172]]
```

```
In [12]: plt.imshow(A_4)
plt.colorbar()
plt.savefig("4-rank Approximation")
plt.show()
```

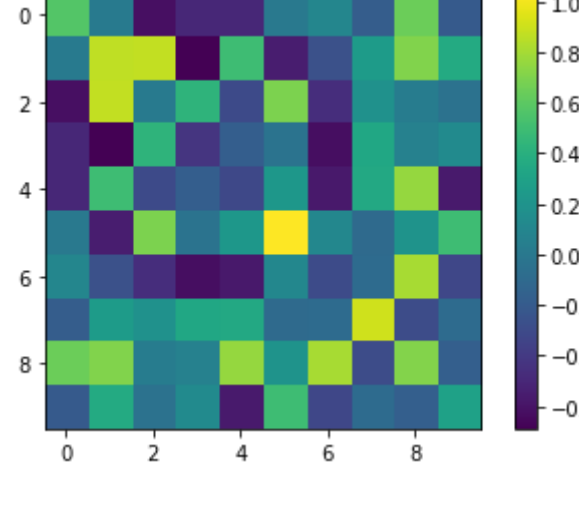
```
In [13]: ## Generating the matrix of the top 2 eigenvalues and the matrices containing the eigenvectors
E_7 = np.zeros((7,7))
np.fill_diagonal(E_7, W[:7])

Q_7 = V[:,0:7]
A_7 = np.dot(np.dot(Q_7, E_7), Q_7.T)
print(A_7)

[[ 0.57295994  0.0138352 -0.6183931 -0.40606276 -0.49527396  0.0054864
 8 0.10341395 -0.18103532  0.65025937 -0.20137206]
 [ 0.0138352  0.86997323  0.87658254 -0.68764862  0.49985527 -0.5485532
 9 -0.25815399  0.25819296  0.70921591  0.36333997]
 [-0.6183931  0.87658254  0.01298693  0.43385516 -0.30116133  0.6951065
 5 -0.4595117  0.1820606  0.03747017 -0.03597403]
 [-0.40606276 -0.68764862  0.43385516 -0.42256837 -0.17159161 -0.0329288
 2
```

```
-0.62201084 0.33678114 0.06797758 0.13538735]
[-0.49527396 0.49985527 -0.30116133 -0.17159161 -0.3117751 0.2225298
5
-0.57083631 0.35142362 0.76413926 -0.56333061]
[ 0.00548648 -0.54855329 0.69510655 -0.03292882 0.22252985 1.0344576
7
0.11061813 -0.09239007 0.19801877 0.50054858]
[ 0.10341395 -0.25815399 -0.4595117 -0.62201084 -0.57083631 0.1106181
3
-0.29101008 -0.08553753 0.81020632 -0.32232761]
[-0.18103532 0.25819296 0.1820606 0.33678114 0.35142362 -0.0923900
7
-0.08553753 0.90740695 -0.29023617 -0.08501399]
[ 0.65025037 0.70921591 0.03747017 0.06797758 0.76413926 0.1980187
7
0.81020632 -0.29023617 0.71727185 -0.16651024]
[-0.20137206 0.36333997 -0.03597403 0.13538735 -0.56333061 0.5005485
8
-0.32232761 -0.08501399 -0.16651024 0.29559776]]
```

```
In [14]: plt.imshow(A_7)
plt.colorbar()
plt.savefig("7-rank Approximation")
plt.show()
```



**Observations and Comments**

The above method works only for square matrices, for general rectangular matrices we need to perform Singular Value Decomposition (SVD). To measure the variance of data represented by the approximation, we can measure the Frobenius norm of the difference of the approximation matrix and the original matrix. The approximated matrix essentially reduces the complexity in terms of dimensionality of the original matrix, as instead of 10 eigenvectors and values, we use the 'top 2' or 'top 4' vectors according to their 'importance'.