

```
In [11]: import numpy as np

from numpy.linalg import inv, eig, svd

A = np.array([
    [4, -2, 2, 1],
    [1, 1, 0, 1],
    [-2, 1, 3, -1],
    [1, 3, -1, 2]
])
```

```
In [12]: # Inverse of A

A_inv = inv(A)
print("Inverse of A:", A_inv)

Inverse of A: [[ 5.0000000e+00 -3.0000000e+01  1.0000000e+00  1.3
0000000e+01]
 [ 4.0000000e+00 -2.5000000e+01  1.0000000e+00  1.1000000e+01]
 [-1.0000000e+00  7.0000000e+00  5.82867088e-16 -3.0000000e+00]
 [-9.0000000e+00  5.6000000e+01 -2.0000000e+00 -2.4000000e+01]]
```

```
In [13]: # Eigenvalues and Eigenvectors

eigenvalues, eigenvectors = eig(A)
print("\nEigenvalues:\n", eigenvalues)
print("\nEigenvectors (columns of P):\n", eigenvectors)

Eigenvalues:
[-0.02231724+0.j           3.6104532 +1.72034086j  3.6104532 -1.7203
4086j
 2.80141085+0.j          ]
[[-0.43676159+0.j           0.57598271+0.j           0.57598271-0.j
 0.26748859+0.j          ]
 [-0.36900111+0.j           0.00962337-0.2105225j  0.00962337+0.2105
225j
 -0.34893941+0.j          ]
 [ 0.10239683+0.j           -0.00821729+0.55142262j -0.00821729-0.5514
226j
 -0.06120796+0.j          ]
 [ 0.81399778+0.j           -0.18869091-0.53300366j -0.18869091+0.5330
0366j
 -0.89607183+0.j          ]]
Eigenvectors (columns of P):
[[[-0.43676159+0.j           0.57598271+0.j           0.57598271-0.j
 0.26748859+0.j          ]
 [-0.36900111+0.j           0.00962337-0.2105225j  0.00962337+0.2105
225j
 -0.34893941+0.j          ]
 [ 0.10239683+0.j           -0.00821729+0.55142262j -0.00821729-0.5514
226j
 -0.06120796+0.j          ]
 [ 0.81399778+0.j           -0.18869091-0.53300366j -0.18869091+0.5330
0366j
 -0.89607183+0.j          ]]
```

In [14]: # Diagonalization

```
P = eigenvectors
D = np.diag(eigenvalues)
P_inv = inv(P)

# Verify A = P D P^-1
A_diagonalized = P @ D @ P_inv
print("\nDiagonalized A (P D P^-1):\n", A_diagonalized)
```

Diagonalized A (P D P⁻¹):

[[4.0000000e+00-1.27549228e-16j	-2.0000000e+00+1.48378393e-16j
2.0000000e+00+1.93217153e-16j	1.0000000e+00-1.17034130e-16j]
[1.0000000e+00+9.11516538e-18j	1.0000000e+00-2.39847431e-17j
-4.14357081e-15+1.91320470e-17j	1.0000000e+00-3.81278032e-17j]
[-2.0000000e+00-4.39044044e-16j	1.0000000e+00+2.43494279e-17j
3.0000000e+00-4.18421915e-17j	-1.0000000e+00-7.35341107e-17j]
[1.0000000e+00-2.67485770e-16j	3.0000000e+00-1.08632006e-16j
-1.0000000e+00-9.16637678e-17j	2.0000000e+00-3.98164530e-17j]]

In [15]: # Check if A_diagonalized ≈ A

```
is_identical = np.allclose(A, A_diagonalized)
print("\nIs A_diagonalized identical to A?", is_identical)
```

Is A_diagonalized identical to A? True

Explanation

Diagonalization is important because it simplifies matrix operations. When a matrix A can be written as $A = P D P^{-1}$, where D is diagonal:

- Powers of A become easy: $A^n = P D^n P^{-1}$
- It reveals the matrix's structure via eigenvalues
- It enables efficient computation in systems of differential equations, quantum mechanics, and PCA

In [16]: # SVD Reconstruction

```
U, S, Vt = svd(A)
```

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In [19]: # Choose a threshold to keep significant singular values

sigma_threshold = 1.0
S_filtered = np.array([s if s > sigma_threshold else 0 for s in S])
A_reconstructed = U @ np.diag(S_filtered) @ Vt

print("Reconstructed A using filtered SVD:\n", A_reconstructed)
print("Is reconstructed A ≈ original A? ", np.allclose(A, A_reconstructed))
```

Reconstructed A using filtered SVD:
[[3.99915045e+00 -2.00070915e+00 2.00019707e+00 1.00158201e+00]
[1.00525801e+00 1.00438901e+00 -1.21971810e-03 9.90208714e-01]
[-2.00018645e+00 9.99844369e-01 3.00004325e+00 -9.99652809e-01]
[9.97733776e-01 2.99810832e+00 -9.99474297e-01 2.00422008e+00]]
Is reconstructed A ≈ original A? False

```
In [ ]:
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