

PROBLEM 3 - Lanczos-Davidson

Gisela Martí Guerrero, ICC 2023

Python program that performs the Lanczos and Lanczos-Davidson diagonalization methods for large matrices applied to Hilbert matrix $N = 100$.

```
In [1]: import numpy as np
        from pandas import *
        import numpy.linalg as la
```

We start by implementing the Lanczos algorithm to generate the representation of a Hermitian $N \times N$ matrix H in a subspace. The Lanczos algorithm is an iterative method for finding a few eigenvalues and corresponding eigenvectors of a Hermitian matrix.

The function first initializes two matrices, L_v for Lanczos vectors and H_k for the Hamiltonian in the subspace, both with dimensions $(len(vg), len(vg))$, where vg is the initial guess vector. This vector is normalized and is set as the first Lanczos vector in the matrix L_v . It then performs the first iteration step of the Lanczos algorithm:

1. It computes the matrix-vector product $w = H \cdot L_v[0]$.
2. It computes the coefficient a as the inner product of the conjugate of w and $L_v[0]$.
3. It updates w to be orthogonal to the first Lanczos vector.
4. It sets the element $H_k[0, 0]$ in the tridiagonal matrix H_k to the value of a .

It then iterates over the remaining Lanczos vectors:

1. It computes the coefficient b based on the norm of w .
2. It normalizes the current Lanczos vector.
3. It updates w to be orthogonal to the current Lanczos vector and the previous one.
4. It computes the coefficients a and b for the tridiagonal matrix H_k .

The function returns (H_k, L_v) , where H_k is the tridiagonal matrix representing the Hamiltonian in the subspace, and L_v is the matrix containing the Lanczos vectors.

```
In [2]: def lanczos(H,vg):
    Lv=np.zeros((len(vg),len(vg)), dtype=complex)
    Hk=np.zeros((len(vg),len(vg)), dtype=complex)
    Lv[0]=vg/la.norm(vg)
    w=np.dot(H,Lv[0])
    a=np.dot(np.conj(w),Lv[0])
    w=w-a*Lv[0]
    Hk[0,0]=a
    for j in range(1,len(vg)):
        b=(np.dot(np.conj(w),np.transpose(w)))*0.5
        Lv[j]=w/b
        w=np.dot(H,Lv[j])
        a=np.dot(np.conj(w),Lv[j])
        w=w-a*Lv[j]-b*Lv[j-1]
        Hk[j,j]=a
        Hk[j-1,j]=b
        Hk[j,j-1]=np.conj(b)

    return (Hk,Lv)
```

Now we define the function "QR", which is the same one used in the previous exercise (Householder diagonalization), to perform a QR decomposition of a given matrix.

```
In [3]: def QR(A):
    n, m = A.shape
    Q = np.empty((n, n))
    u = np.empty((n, n))
    u[:, 0] = A[:, 0]
    Q[:, 0] = u[:, 0] / np.linalg.norm(u[:, 0])

    for i in range(1, n):
        u[:, i] = A[:, i]
        for j in range(i):
            u[:, i] -= (A[:, i] @ Q[:, j]) * Q[:, j]
        Q[:, i] = u[:, i] / np.linalg.norm(u[:, i])
    R = np.zeros((n, m))
    for i in range(n):
        for j in range(i, m):
            R[i, j] = A[:, j] @ Q[:, i]

    return Q, R
```

The same way, the function "eigenvalues" is also used using the same code from the previous exercise to find the eigenvalues of the given matrix using the QR decomposition method.

```
In [4]: def eigenvalues(A):
    A_old = np.copy(A)
    A_new = np.copy(A)
    diff = np.inf
    i = 0
    while (diff > tolerance) and (i < max_iter):
        A_old[:, :] = A_new
        Q, R = QR(A_old)
        A_new[:, :] = R @ Q
        diff = np.abs(A_new - A_old).max()
        i += 1
    eigvals = np.diag(A_new)
    return eigvals
```

The Hilbert matrix is now defined in the following function, taking N as an input parameter

```
In [5]: def hilbert(n):
        H_matrix = np.array([[1.0 / (i+j-1) for j in range(1, n+1)] for i in range(1, n+1)])
        return H_matrix
```

```
In [6]: # Define parameters
        tolerance = 1.0e-9
        max_iter = 1000

        # Hilbert matrix
        N = 100
        HM = hilbert(N)

        print("Input matrix:")
        cols = ['c{}'.format(i) for i in range(1, 101)]
        rows = ['r{}'.format(i) for i in range(1, 101)]
        print(DataFrame(HM, columns=cols, index=rows))
```

Input matrix:

	c1	c2	c3	c4	c5	c6	c7	\
r1	1.000000	0.500000	0.333333	0.250000	0.200000	0.166667	0.142857	
r2	0.500000	0.333333	0.250000	0.200000	0.166667	0.142857	0.125000	
r3	0.333333	0.250000	0.200000	0.166667	0.142857	0.125000	0.111111	
r4	0.250000	0.200000	0.166667	0.142857	0.125000	0.111111	0.100000	
r5	0.200000	0.166667	0.142857	0.125000	0.111111	0.100000	0.090909	
...	
r96	0.010417	0.010309	0.010204	0.010101	0.010000	0.009901	0.009804	
r97	0.010309	0.010204	0.010101	0.010000	0.009901	0.009804	0.009709	
r98	0.010204	0.010101	0.010000	0.009901	0.009804	0.009709	0.009615	
r99	0.010101	0.010000	0.009901	0.009804	0.009709	0.009615	0.009524	
r100	0.010000	0.009901	0.009804	0.009709	0.009615	0.009524	0.009434	

	c8	c9	c10	...	c91	c92	c93	\
r1	0.125000	0.111111	0.100000	...	0.010989	0.010870	0.010753	
r2	0.111111	0.100000	0.090909	...	0.010870	0.010753	0.010638	
r3	0.100000	0.090909	0.083333	...	0.010753	0.010638	0.010526	
r4	0.090909	0.083333	0.076923	...	0.010638	0.010526	0.010417	
r5	0.083333	0.076923	0.071429	...	0.010526	0.010417	0.010309	
...	
r96	0.009709	0.009615	0.009524	...	0.005376	0.005348	0.005319	
r97	0.009615	0.009524	0.009434	...	0.005348	0.005319	0.005291	
r98	0.009524	0.009434	0.009346	...	0.005319	0.005291	0.005263	
r99	0.009434	0.009346	0.009259	...	0.005291	0.005263	0.005236	
r100	0.009346	0.009259	0.009174	...	0.005263	0.005236	0.005208	

	c94	c95	c96	c97	c98	c99	c100	
r1	0.010638	0.010526	0.010417	0.010309	0.010204	0.010101	0.010000	
r2	0.010526	0.010417	0.010309	0.010204	0.010101	0.010000	0.009901	
r3	0.010417	0.010309	0.010204	0.010101	0.010000	0.009901	0.009804	
r4	0.010309	0.010204	0.010101	0.010000	0.009901	0.009804	0.009709	
r5	0.010204	0.010101	0.010000	0.009901	0.009804	0.009709	0.009615	
...	
r96	0.005291	0.005263	0.005236	0.005208	0.005181	0.005155	0.005128	
r97	0.005263	0.005236	0.005208	0.005181	0.005155	0.005128	0.005102	
r98	0.005236	0.005208	0.005181	0.005155	0.005128	0.005102	0.005076	
r99	0.005208	0.005181	0.005155	0.005128	0.005102	0.005076	0.005051	
r100	0.005181	0.005155	0.005128	0.005102	0.005076	0.005051	0.005025	

[100 rows x 100 columns]

A random vector v of length N is generated to initialize the Lanczos algorithm with an arbitrary initial guess. Then the Lanczos algorithm is applied to the Hilbert matrix HM using the random vector v . The resulting tridiagonal matrix is stored in T , and the Lanczos vectors are stored in V . The "eigenvalues" function is called with the real part of the tridiagonal matrix T as its argument, to get the eigenvalues of the matrix.

```
In [7]: v_rand = np.random.random(N)
        T,V = lanczos(HM.copy(),v_rand)
        eigenval = eigenvalues(T.real)
```

```
In [8]: print("Tridiagonal matrix:")
print(DataFrame(T.real, columns=cols, index=rows))
print("")
print("Eigenvalues:")
print(eigenval)
```

Tridiagonal matrix:

	c1	c2	c3	c4	c5	c6	c7	c8	\
r1	1.034562	0.930871	0.000000	0.000000	0.000000	0.000000	0.0	0.0	
r2	0.930871	1.245887	0.513891	0.000000	0.000000	0.000000	0.0	0.0	
r3	0.000000	0.513891	0.725001	0.120593	0.000000	0.000000	0.0	0.0	
r4	0.000000	0.000000	0.120593	0.211738	0.037631	0.000000	0.0	0.0	
r5	0.000000	0.000000	0.000000	0.037631	0.054833	0.00068	0.0	0.0	
...	
r96	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	
r97	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	
r98	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	
r99	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	
r100	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0	0.0	

	c9	c10	...	c91	c92	c93	c94	c95	c96	c97	\
r1	0.0	0.0	...	0.0	0.0	0.0	0.0	0.000000	0.000000	0.000000	
r2	0.0	0.0	...	0.0	0.0	0.0	0.0	0.000000	0.000000	0.000000	
r3	0.0	0.0	...	0.0	0.0	0.0	0.0	0.000000	0.000000	0.000000	
r4	0.0	0.0	...	0.0	0.0	0.0	0.0	0.000000	0.000000	0.000000	
r5	0.0	0.0	...	0.0	0.0	0.0	0.0	0.000000	0.000000	0.000000	
...	
r96	0.0	0.0	...	0.0	0.0	0.0	0.0	0.351655	0.264636	0.000019	
r97	0.0	0.0	...	0.0	0.0	0.0	0.0	0.000000	0.000019	0.819166	
r98	0.0	0.0	...	0.0	0.0	0.0	0.0	0.000000	0.000000	0.042950	
r99	0.0	0.0	...	0.0	0.0	0.0	0.0	0.000000	0.000000	0.000000	
r100	0.0	0.0	...	0.0	0.0	0.0	0.0	0.000000	0.000000	0.000000	

	c98	c99	c100
r1	0.000000	0.000000	0.000000
r2	0.000000	0.000000	0.000000
r3	0.000000	0.000000	0.000000
r4	0.000000	0.000000	0.000000
r5	0.000000	0.000000	0.000000
...
r96	0.000000	0.000000	0.000000
r97	0.042950	0.000000	0.000000
r98	0.012315	0.000423	0.000000
r99	0.000423	0.047544	0.009657
r100	0.000000	0.009657	0.239817

[100 rows x 100 columns]

Eigenvalues:

[2.18269610e+00	2.18269610e+00	2.18269610e+00	2.18269610e+00
	2.18269610e+00	2.18269610e+00	2.18269610e+00	2.18269610e+00
	2.18269610e+00	2.18269610e+00	2.18269610e+00	2.18269610e+00
	2.18269610e+00	2.18269610e+00	2.18269610e+00	2.18269610e+00
	2.18269610e+00	8.21445561e-01	8.21445561e-01	8.21445561e-01
	8.21445561e-01	8.21445561e-01	8.21445561e-01	8.21445561e-01
	8.21445561e-01	8.21445561e-01	8.21445561e-01	8.21445561e-01
	8.21445561e-01	8.21445561e-01	8.21445561e-01	8.21445560e-01
	2.18595882e-01	2.18595882e-01	2.18595882e-01	2.18595882e-01
	2.18595882e-01	2.18595882e-01	2.18595882e-01	2.18595882e-01
	2.18595882e-01	2.18595882e-01	2.40348322e-01	2.18595882e-01
	2.18595882e-01	2.18595882e-01	4.92922510e-02	4.92922510e-02
	4.92922510e-02	4.92922510e-02	4.92922510e-02	4.92922510e-02

4.92922510e-02	4.92922510e-02	4.92922510e-02	4.92922510e-02
4.70751606e-02	1.00318122e-02	1.00318122e-02	1.00318122e-02
1.00318122e-02	1.00318122e-02	1.00318122e-02	1.00318122e-02
1.00318122e-02	1.00307683e-02	1.88506328e-03	1.88506328e-03
1.88506328e-03	1.88506328e-03	1.88506328e-03	1.88506328e-03
1.88506315e-03	3.30867810e-04	3.30867811e-04	3.30867809e-04
3.30867812e-04	3.30867811e-04	3.30842750e-04	5.46452976e-05
5.46453026e-05	5.46453018e-05	5.46453039e-05	5.44585027e-05
4.09338768e-05	-1.70009293e-05	8.53626581e-06	8.53628286e-06
8.53628272e-06	8.53906605e-06	-3.44355469e-06	4.74495695e-07
1.01027334e-06	1.26617626e-06	1.26617685e-06	1.26615904e-06
1.78868744e-07	1.79046810e-07	2.41612430e-08	4.65601614e-09]