Assignment 3 - Numerical Linear Algebra

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Abstract

We design and test a function to_hessemberg(A) that reduces an arbitrary square matrix to (upper) Hessenberg form with Householder reflectors, returns the reflector vectors, the compact Hessenberg matrix H, and the accumulated orthogonal factor Q, verifying numerically that $A = QHQ^*$ and $Q^*Q = I$ for symmetric and nonsymmetric inputs of orders 10 - 10000. Timings confirm the expected O(something) cost and reveal the $2 \times \text{speed-up}$ attainable for symmetric matrices through trivial bandwidth savings. Leveraging this routine, we investigate the spectral structure of orthogonal matrices: we show that all eigenvalues lie on the unit circle, analyse the consequences for the power method and inverse iteration, and obtain a closed-form spectrum for generic 2×2 orthogonals. Random 4×4 orthogonal matrices generated via QR factorisation are then reduced to Hessenberg form; the eigenvalues of their trailing 2×2 blocks are computed analytically and reused as fixed shifts in the QR iteration, where experiments demonstrate markedly faster convergence. Throughout, every algorithm is documented and supported by commented plots that corroborate the theoretical claims.

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1. Introduction

One could calculate the eigenvalues of a square matrix using the following algorithm:

- 1. Compute the n-th degree polynomial $\det(A \lambda I) = 0$,
- 2. Solve for λ (somehow).

On step 2, the eigenvalue problem would have been reduced to a polynomial root-finding problem, which is awful and extremely ill-conditioned. From the previous assignment we know that in the denominator of the relative condition number $\kappa(x)$ there's a |x-n|. So $\kappa(x)\to\infty$ when $x\to 0$. As an example, consider the polynomial

$$p(x) = (x-2)^9 = x^9 - 18x^8 + 144x^7 - 672x^6 + 2016x^5$$
$$-4032x^4 + 5376x^3 - 4608x^2 + 2304x - 512$$
 (1)

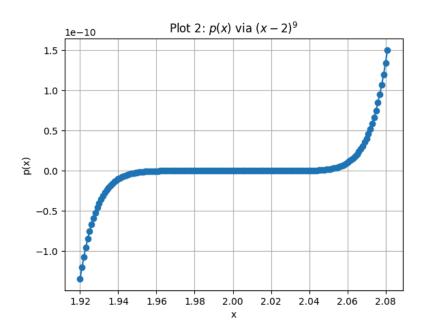


Figure 1: p(x) via the coefficients in eq. (1)

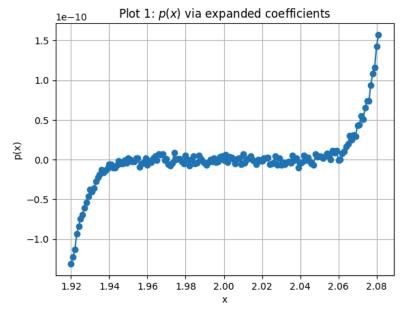


Figure 2: p(x) via $(x-2)^9$

<u>Figure 2</u> shows a smooth curve, while <u>Figure 1</u> shows a weird oscillation around x = 0 (And pretty much everywhere else if the reader is sufficiently persistent).

This is due to the round-off errors when $x\approx 0$ and the big coefficients of the polynomial. In general, polynomial are very sensitive to perturbations in the coefficients, which is why rootfinding is a bad idea to find eigenvalues.

Here we discuss aspects of some iterative eigenvalue algorithms, such as power iteration, inverse iteration, and QR iteration.

2. Hessemberg Reduction (Problem 1)

2.1. Calculating the Householder Reflectors (a)

The following packages will be used in the next functions:

```
1 import numpy as np
2 import matplotlib.pyplot as plt
3 from scipy.linalg import hessenberg, qr, eig
4 import time
5 from typing import List, Tuple
6 import pandas as pd
7 import math
8 from IPython.display import display, Markdown
9 from ast import literal_eval
```

The following function calculates the Householder reflectors that reduce a matrix to Hessenberg form. It returns the reflector vectors, the compact Hessenberg matrix H, and the accumulated orthogonal factor Q.

```
Python
1
     def build_householder_unit_vector(
2
             target_vector: np.ndarray
3
     ) -> np.ndarray:
4
5
         Builds a Householder unit vector
6
7
8
         Args:
             1. target vector (np.ndarray): Column vector that we want to annihilate
9
             (size \geq 1).
10
11
         Returns:
12
                  The normalised Householder vector (\|v\|_2 = 1) with a real first
13
                  component.
14
15
         Raises:

    ValueError: If 'target_vector' has zero length.

16
17
18
```

```
19
         if target_vector.size == 0:
20
             raise ValueError("The target vector is empty; no reflector needed.")
21
22
        vector norm: float = np.linalg.norm(target vector)
23
         if vector norm == 0.0: #nothing to annihilate - return canonical basis
24
         vector
25
             householder vector: np.ndarray = np.zeros like(target vector)
26
             householder vector[0] = 1.0
27
             return householder_vector
28
29
         sign correction: float = (
30
             1.0 if target_vector[0].real >= 0.0 else -1.0
31
32
         copy_of_target_vector: np.ndarray = target_vector.copy()
33
         copy_of_target_vector[0] += sign_correction * vector_norm
34
         householder_vector: np.ndarray = (
35
             copy_of_target_vector / np.linalg.norm(copy_of_target_vector)
36
         )
37
         return householder_vector
38
39
40
    def to_hessenberg(
41
             original matrix: np.ndarray,
42
    ) -> Tuple[List[np.ndarray], np.ndarray, np.ndarray]:
43
44
        Reduce 'original_matrix' to upper Hessenberg form by Householder
45
         reflections.
46
47
        Args
             1. original matrix (np.ndarray): Real or complex square matrix of order
48
             'matrix order'.
49
50
        Returns
51
             Tuple consisting of:
52
53
             1. householder reflectors list (List[np.ndarray])
             2. hessenberg matrix (np.ndarray)
54
             accumulated_orthogonal_matrix (np.ndarray) s.t.
55
               original matrix = Q \cdot H \cdot Q^H
56
57
        Raises
58
59
            1. ValueError: If 'original matrix' is not square.
         0.00
60
61
```

```
62
        working_matrix: np.ndarray = np.asarray(original_matrix).copy()
63
64
        if working matrix.shape[0] != working matrix.shape[1]:
65
             raise ValueError("Input matrix must be square.")
66
67
        matrix order: int = working matrix.shape[0]
68
        accumulated_orthogonal_matrix: np.ndarray = np.eye(
69
            matrix order, dtype=working matrix.dtype
70
        )
71
        householder reflectors list: List[np.ndarray] = []
72
        for column_index in range(matrix_order - 2): #extract the part of column
73
         'column_index' that we want to zero out
74
            target_column_segment: np.ndarray = working_matrix[
75
                 column_index + 1 :, column_index
76
            1
77
78
            householder_vector: np.ndarray = build_householder_unit_vector(
79
                 target column segment
            ) #build Householder vector for this segment
80
            householder reflectors list.append(householder vector)
81
82
83
            #expand it to the full matrix dimension
84
            expanded householder vector: np.ndarray = np.zeros(
85
                 matrix_order, dtype=working_matrix.dtype
86
            )
87
            expanded_householder_vector[column_index + 1 :] = householder_vector
88
89
            working_matrix -= 2.0 * np.outer(
90
91
                 expanded_householder_vector,
92
                 expanded_householder_vector.conj().T @ working_matrix,
93
            ) #apply reflector from BOTH sides
94
            working matrix -= 2.0 * np.outer(
                 working_matrix @ expanded_householder_vector,
95
                 expanded_householder_vector.conj().T,
96
97
98
            #accumulate 0
99
            accumulated orthogonal matrix -= 2.0 * np.outer(
100
101
                 accumulated_orthogonal_matrix @ expanded_householder_vector,
                 expanded householder vector.conj().T,
102
103
104
105
        hessenberg matrix: np.ndarray = working matrix
106
        return (
```

```
householder_reflectors_list,
hessenberg_matrix,
accumulated_orthogonal_matrix,

)
```

We will evaluate this function in Section 2.2.

2.2. Evaluating the Function (b), (c), (d)

We present another algorithm for evaluating the function to_hessenberg(A) for random matrices of various sizes, inputed by the user, which also gets to choose if symmetric matrices will be generated or not.

```
1
     #RANDOM MATRIX GENERATOR
                                                                               Python
2
     def generate_random_matrix(n:int, distribution:str="normal",
3
                                 symmetric:bool=False, seed:int|None=None):
4
         rng = np.random.default_rng(seed)
5
         if distribution == "normal":
             A = rng.standard_normal((n, n))
6
        elif distribution == "uniform":
7
             A = rng.uniform(-1.0, 1.0, size=(n, n))
8
9
         else:
             raise ValueError("distribution must be 'normal' or 'uniform'")
10
11
         return (A + A.T) / 2.0 if symmetric else A
12
13
     #REFLECTOR CALCULATOR
14
     def house_vec(x:np.ndarray) -> np.ndarray:
15
16
         11 11 11
17
18
         Builds a Householder reflector for a given column vector x.
19
         Args:
20
             x (np.ndarray): Column vector to be transformed.
21
         Returns:
22
             np.ndarray: Normalised Householder vector with a real first component.
23
         Raises:
24
             None
         11 11 11
25
26
27
         sigma = np.linalg.norm(x)
         if sigma == 0.0:
28
29
             el = np.zeros like(x)
30
             e1[0] = 1.0
31
             return el
32
         sign = 1.0 if x[0].real >= 0.0 else -1.0
33
         v = x.copy()
34
         v[0] += sign * sigma
35
         return v / np.linalg.norm(v)
```

```
36
    def hessenberg reduction(A in:np.ndarray, symmetric:bool=False,
37
    accumulate q:bool=True):
38
39
40
         Reduces a matrix to upper Hessenberg form using Householder reflections.
41
        Args:
42
            A in (np.ndarray): Input matrix to be reduced.
            symmetric (bool): If True, treat the matrix as symmetric and reduce to
43
            tridiagonal form.
            accumulate q (bool): If True, accumulate the orthogonal matrix Q.
44
45
         Returns:
            Tuple[np.ndarray, np.ndarray]: The reduced matrix in Hessenberg form
46
            and the orthogonal matrix Q.
47
        Raises:
48
            None
         0.0.0
49
50
51
        A = A_in.copy()
        n = A.shape[0]
52
53
        Q = np.eye(n, dtype=A.dtype)
54
55
         if not symmetric:
                              #GENERAL caSe
            for k in range(n-2):
56
57
                 v = house vec(A[k+1:, k])
                 w = np.zeros(n, dtype=A.dtype)
58
59
                 w[k+1:] = v
60
                 A = 2.0 * np.outer(w, w.conj().T @ A)
61
                 A = 2.0 * np.outer(A @ w, w.conj().T)
62
                 if accumulate q:
63
                     Q = 2.0 * np.outer(Q @ w, w.conj().T)
64
            return A, Q
65
66
         #SYMMETRIC TRIDIAGONAL CASE
67
         for k in range(n-2):
68
            x = A[k+1:, k]
69
            v = house_vec(x)
70
            beta = 2.0
71
            w = A[k+1:, k+1:] @ v #trailing submatrix rank-2 update (A \leftarrow A - v w
72
            - W V^{T}
73
            tau = beta * 0.5 * (v @ w)
74
            w -= tau * v
75
            A[k+1:, k+1:] -= beta * np.outer(v, w) + beta * np.outer(w, v)
76
            new_val = -np.sign(x[0]) * np.linalg.norm(x) #store the single sub-
77
            diagonal element, zero the rest
```

```
78
             A[k+1, k] = new_val
79
             A[k, k+1] = new val
80
             A[k+2:, k] = 0.0
81
             A[k, k+2:] = 0.0
82
83
             if accumulate q: #accumulate Q if requested
84
                 Q[:, k+1:] -= beta * np.outer(Q[:, k+1:] @ v, v)
85
86
         A = np.triu(A) + np.triu(A, 1).T #force symmetry
87
         return A, Q
88
89
90
    #VERIFYING PART
91
    def verify factorisation once(n:int, dist:str, symmetric:bool, seed:int|None):
92
         11 11 11
93
         Verifies the factorisation of a random matrix of size n.
94
95
         Args:
             n (int): Size of the matrix.
96
97
             dist (str): Distribution type ('normal' or 'uniform').
             symmetric (bool): Whether the matrix is symmetric.
98
99
             seed (int | None): Random seed for reproducibility.
100
        Returns:
101
             None
102
        Raises:
103
             None
         11 11 11
104
105
106
        A = generate random matrix(n, dist, symmetric, seed)
107
        T, Q = hessenberg_reduction(A, symmetric=symmetric)
108
         res fact = np.linalg.norm(A - Q @ T @ Q.T)
109
         res_orth = np.linalg.norm(Q.T @ Q - np.eye(n))
110
         colour = "green" if res_fact < 1e-11 else "red"</pre>
         typ = "symmetric" if symmetric else "general"
111
112
         display(Markdown(
113
             f"**{n}×{n} {typ}** \n"
             f"<span style='color:\{colour\}'>||A - Q T Q^T|| = \{res_fact:.2e\}</span>
114
             f''||Q^TQ - I|| = \{res_orth:.2e\}''
115
116
        ))
117
118
    def benchmark_hessenberg(size_list, dist:str, mode:str, seed:int|None,
119
     reps small:int=5):
120
         11 11 11
121
```

```
122
         Benchmark the Hessenberg reduction for various matrix sizes and types.
123
         Args:
124
             size list (list of int): List of matrix sizes to test.
125
             dist (str): Distribution type ('normal' or 'uniform').
126
             mode (str): Matrix type ('general', 'symmetric', or 'both').
127
             seed (int | None): Random seed for reproducibility.
128
             reps_small (int): Number of repetitions for small matrices.
129
         Returns:
130
             pd.DataFrame: DataFrame containing the benchmark results.
131
        Raises:
132
             None
         11 11 11
133
134
135
         records = []
136
         for n in size list:
137
             for sym in ([False, True] if mode=="both" else [mode=="symmetric"]):
138
                 A = generate_random_matrix(n, dist, sym, seed)
139
140
                 t0 = time.perf counter()
141
                 hessenberg_reduction(A, symmetric=sym, accumulate_q=False)
                 probe = time.perf counter() - t0
142
                 reps = reps_small if probe*reps_small >= 1.0 else math.ceil(1.0 /
143
                 probe)
144
145
                 times = []
146
                 for _ in range(reps):
147
                     start = time.perf counter()
148
                     hessenberg_reduction(A, symmetric=sym, accumulate_q=False)
                     times.append(time.perf counter() - start)
149
150
151
                 records.append(dict(size=n,
                                     type="symmetric" if sym else "general",
152
153
                                      reps=reps,
154
                                     avg=np.mean(times)))
155
156
         df = pd.DataFrame(records)
157
         display(df.style.format({"avg":"{:.3e}"}).hide(axis="index"))
158
159
         plt.figure(figsize=(7,5))
         mark = {"general":"o", "symmetric":"s"}
160
161
         for label, sub in df.groupby("type"):
             plt.loglog(sub["size"], sub["avg"], marker=mark[label], ls="-",
162
             label=label)
             if len(sub) > 1:
163
164
                 a,b = np.polyfit(np.log10(sub["size"]), np.log10(sub["avg"]), 1)
165
                 plt.loglog(sub["size"], 10**(b+a*np.log10(sub["size"])),
```

```
166
                          "--", label=f"{label} fit \sim $n^{a:.2f}$")
167
        plt.xlabel("matrix size (log)")
168
        plt.ylabel("runtime [s] (log)")
169
        plt.title("Hessenberg (general) vs Tridiagonal (symmetric)")
170
        plt.grid(True, which="both", ls=":")
171
        plt.legend(); plt.tight_layout(); plt.show()
172
        return df
173
174
176 try:
177
        raw = input("\nMatrix sizes (Python list) (e.g): [64,128,256,512,1024]: ")
178
        sizes = literal eval(raw) if raw.strip() else [64,128,256,512,1024]
179 except Exception:
        print("Bad list -> using default.")
180
181
        sizes = [64, 128, 256, 512, 1024]
182
    dist = input("Distribution ('normal'/'uniform') [normal]: ").strip().lower()
183
    or "normal"
    mode_txt = input("Matrix type g=general, s=symmetric, b=both [g]:
184
    ").strip().lower() or "g"
185 mode = "symmetric" if mode_txt=="s" else "both" if mode_txt=="b" else "general"
186 seed_txt = input("Random seed (None/int) [None]: ").strip()
187 seed_val = None if seed_txt.lower() in {"", "none"} else int(seed_txt)
188
189 # accuracy on *all* requested sizes
190 for n in sizes:
        for sym in ([False, True] if mode=="both" else [mode=="symmetric"]):
191
192
            verify_factorisation_once(n, dist, sym, seed_val)
193
194
195 benchmark hessenberg(sizes, dist, mode, seed val)
```

The reader should be aware that my poor <u>Dell Inspiron 5590</u> has crashed precisely 5 times while i was writing this (i might have tried with matrices of order $10^6 \times 10^6$). Unfortunately the runtime was around 4 minutes for a matrix $A \approx 10^3 \times 10^3$.

An expected output is:

```
1 64×64 general
2 ||A - Q T Q<sup>T</sup>|| = 7.51e-14
3 ||Q<sup>T</sup>Q - I|| = 7.07e-15
4
5 64×64 symmetric
6 ||A - Q T Q<sup>T</sup>|| = 4.83e-14
7 ||Q<sup>T</sup>Q - I|| = 7.39e-15
8
9 128×128 general
```

```
10 \|A - Q T Q^{T}\| = 1.84e-13
11 \|Q^TQ - I\| = 1.26e-14
12
13 128×128 symmetric
14 \|A - Q T Q^{T}\| = 1.14e-13
15 \|Q^TQ - I\| = 1.25e-14
16
18 \|A - Q T Q^{T}\| = 4.70e-13
19 \|Q^TQ - I\| = 2.28e-14
20
21 256×256 symmetric
22 \|A - Q T Q^{T}\| = 2.78e-13
23 \|Q^TQ - I\| = 2.25e-14
24
26 \|A - Q T Q^{\mathsf{T}}\| = 1.16e-12
27 \|Q^TQ - I\| = 4.10e-14
28
29 512×512 symmetric
30 \|A - Q T Q^{T}\| = 7.10e-13
31 \|Q^TQ - I\| = 4.09e-14
32
33 1024×1024 general
34 \|A - Q T Q^{T}\| = 3.05e-12
35 \|Q^TQ - I\| = 7.57e-14
36
37 1024×1024 symmetric
38 \|A - Q T Q^{T}\| = 1.84e-12
39 \|Q^TQ - I\| = 7.64e-14
```

As n grows, we observe that the residuals also grow, but still in machine precision. The difference between the symmetric and nonsymmetric cases are more pronounced in larger matrices.

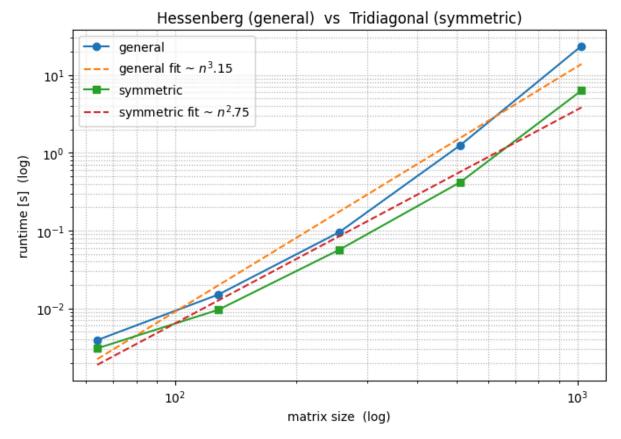


Figure 3: Runtime of the Hessenberg reduction for ordinary and symmetric matrices

2.2.1. Complexity (c)

Figure 3 shows the expected $O(n^3)$ complexity for the general case and $O(n^2)$ for the symmetric case. The latter is better discussed in Section 2.2.2.

To understand why the complexity is $O(n^3)$ in the general case, we can look at the algorithm. The outer loop runs n-2 times, and inside it, we have two matrix-vector products and two outer products, which are all $O(n^2)$. Thus, the total complexity is $O(n^3)$.

2.2.2. The Symmetric Case (d)

On the symmetric case we know that reflectors will be applied in only one side of the matrix, since $v^TA = Av^T$. That is precisely what the function generate_random_matrix does. Which cuts complexity from the expected $O(n^3)$ seen in the previous section to a $O(n^2)^2$. [1]

3. Eigenvalues and Iterative Methods

3.1. Power iteration

The power iteration consists on computing large powers of the sequence:

$$\frac{x}{\|x\|}, \frac{Ax}{\|Ax\|}, \frac{A^2x}{\|A^2x\|}, ..., A \in \mathbb{C}^{m \times m} \tag{2}$$

To see why this sequence converges (under good assumptions), let A be diagonalizable. And write:

²See page 194 of <u>Trefethen & Bau's Numerical Linear Algebra book</u>

$$x = \sum_{i=1}^{m} \varphi_i v_i \tag{3}$$

In a basis of eigenvectors v_i with respective eigenvalues $\lambda_i.$ Then for $x\in\mathbb{C}^m$ we have:

$$Ax = \sum_{i=1}^{m} \lambda_i \varphi_i v_i \tag{4}$$

Or even better:

$$A^n x = \sum_{i=1}^m \lambda_i^n \varphi_i v_i \tag{5}$$

Let v_j be the eigenvector associated to the biggest eigenvalue λ_j , then we have:

$$A^n x = \frac{1}{\lambda_j^n} \cdot \sum_{i=1}^m \lambda_i^n \varphi_i v_i = \frac{\lambda_1^n}{\lambda_j^n} \varphi_1 v_1 + \ldots + \varphi_j v_j + \ldots + \frac{\lambda_m^n}{\lambda_j^n} \varphi_m v_m \tag{6}$$

When $n \to \infty$ all of the smaller $\frac{\lambda_k}{\lambda_j}$ will approach 0, so we have:

$$\lim_{n \to \infty} A^n x = \varphi_j v_j \tag{7}$$

So the denominator on the original expression becomes

$$||A^n x|| = ||\varphi_j v_j|| = |\varphi_j| ||v_j|| \tag{8}$$

And the limit is:

$$\lim_{n \to \infty} \frac{A^n x}{\|A^n x\|} = \frac{\varphi_j v_j}{\|\varphi_j\| \|v_j\|} \tag{9}$$

Since $\frac{\varphi_j}{|\varphi_j|}=\pm 1$, the sequence converges to the eigenvector v_j associated to the eigenvalue λ_j .

3.2. Inverse Iteration

Consider $\mu \in \mathbb{R} \setminus \Lambda$, where Λ is the set of eigenvalues of A. The eigenvalues $\hat{\lambda}$ of $(A - \mu I)^{-1}$ are:

$$\begin{split} \det \left(A - \mu I - \hat{\lambda} I \right) &= 0 \Leftrightarrow \det \left(A - \left(\mu + \hat{\lambda} \right) I \right) = 0 \\ \Leftrightarrow \hat{\lambda}_j &= \frac{1}{\lambda_j - \mu} \end{split} \tag{10}$$

Where λ_j are the eigenvalues of A. So if μ is close to an eigenvalue, then $\hat{\lambda}$ will be large. Power iteration seems interesting here, so the sequence:

$$\frac{x}{\|x\|}, \frac{(A-\mu I)^{-1}x}{\|(A-\mu I)^{-1}x\|}, \frac{(A-\mu I)^{-2}x}{\|(A-\mu I)^{-2}x\|}, \dots$$
(11)

Converges to the eigenvector associated to the eigenvalue $\hat{\lambda}$.

4. Orthogonal Matrices (Problem 2) (a)

Here we will discuss how orthogonal matrices behave when we apply the iterations discussed in Section 3.1, and Section 3.2.

So let $Q \in \mathbb{C}^{m \times m}$ be an orthogonal matrix. We are interested in its eigenvalues λ . We know that:

$$Qx = \lambda x \Leftrightarrow x^T Q x = \lambda x^T x$$

$$\Leftrightarrow Q\langle x, x \rangle = \lambda \langle x, x \rangle$$
(12)

Since Q preserves inner product, we have:

$$Q\langle x, x \rangle = \lambda \langle x, x \rangle \Leftrightarrow \langle x, x \rangle = \lambda \langle x, x \rangle$$

$$\Leftrightarrow |\lambda| = 1$$
(13)

So λ lies in the unit circle, i.e $\lambda=e^{i\varphi}, \varphi\in\mathbb{R}$. We now discuss how this affects efficiency of some iterative methods

4.1. Orthogonal Matrices and the Power Iteration

The power method is better discussed in <u>Section 3.1</u>. Here we will write straight forward the result:

$$Q^n x = \frac{1}{\lambda_j^n} \cdot \sum_{i=1}^m \lambda_i^n \varphi_i v_i \tag{14}$$

Where λ_i are the eigenvalues of $Q \in \mathbb{C}^{m \times m}$, φ_i are the coefficients of the expansion of x in the basis of eigenvectors v_i . Since we have that $|\lambda_i| = 1$, we have:

The fact that $|\lambda_i| = 1 \Rightarrow |\lambda_i^n| = 1$ is sufficiently enough for one to be convinced that power iteration does not converge.

Let $\lambda_k = e^{i\psi_k}$, where $\psi_k \in \mathbb{R}$. Then expanding eq. (14):

$$Q^n x = \frac{1}{e^{i\psi_j \cdot n}} \cdot \sum_{\tau=1}^m e^{i\psi_\tau n} \varphi_\tau v_\tau \tag{15}$$

When $n \to \infty$ if $\lambda_j = 1$ then we have:

$$Q^n x = \varphi_j v_j + \sum_{\tau \neq j} e^{i\psi_\tau n} \varphi_\tau v_\tau \tag{16}$$

Since no eigenvalue dominates other eigenvalues in the orthogonal case, usually power iteration fails.

4.2. Orthogonal Matrices and Inverse Iteration

If we apply inverse iteration to an orthogonal matrix with a shift μ , we have:

$$\det(Q - \mu I - \hat{\lambda}I) = 0 \Leftrightarrow \det(Q - (\mu + \hat{\lambda})I) = 0$$

$$\Leftrightarrow \hat{\lambda}_j = \frac{1}{\lambda_j - \mu}$$
(17)

We know that the eigenvalues of Q are on the unit circle, so if μ is close to an eigenvalue λ_j , $\hat{\lambda_j}$ will be huge (dominant), which makes power iteration converge to the eigenvector associated to $\hat{\lambda_j}$, which is the eigenvector associated to λ_j . The fact that the eigenvalues are on the unit circle also contributes to the convergence of the method.

So we concude that inverse iteration works well for orthogonal matrices, if μ is close to an eigenvalue of Q.

4.3. The 2×2 Case (b)

We will calculate the eigenvalues of:

$$A = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \tag{18}$$

With $a, b, c, d \in \mathbb{R}$. The characteristic polynomial gives us:

$$\det(A - \lambda I) = 0 \Leftrightarrow \det\begin{pmatrix} a - \lambda & b \\ c & d - \lambda \end{pmatrix} = 0$$

$$\Leftrightarrow (a - \lambda)(d - \lambda) - bc = 0 \Leftrightarrow \lambda^2 + \lambda(-a - d) + (ad - bc) = 0$$

$$\Leftrightarrow \lambda = (a + d) \pm \frac{\sqrt{(a + d)^2 - 4(ad - bc)}}{2}$$
(19)

So the eigenvalues are:

$$\begin{split} \lambda_1 &= \frac{a + d + \sqrt{(a+d)^2 - 4(ad-bc)}}{2} \\ \lambda_2 &= \frac{a + d - \sqrt{(a+d)^2 - 4(ad-bc)}}{2} \end{split} \tag{20}$$

4.4. Random Orthogonal Matrices (c)

This code generates orthogonal matrices of order 4×4 generated by the QR factorization of random matrices, and reduces the to Hessenberg form. The eigenvalues of the bottom-right 2×2 block are analytically calculated using Section 4.3.

```
Python
1
    def generate_orthogonal_matrix_qr(n=4, seed=None):
2
        11 11 11
3
4
        Generates a random orthogonal matrix using QR decomposition.
5
        Args:
6
             n (int): Size of the matrix (n x n).
7
             seed (int | None): Random seed for reproducibility.
8
        Returns:
9
             np.ndarray: An n x n orthogonal matrix.
10
        Raises:
11
             None
        0.00
12
13
14
        if seed is not None:
15
             np.random.seed(seed)
        A = np.random.randn(n, n)
16
17
        Q, \underline{\hspace{0.2cm}} = np.linalg.qr(A)
18
        return Q
19
    def analytical_eigenvalues_2x2(a, b, c, d):
20
21
22
23
        Calculates the eigenvalues of a 2x2 matrix analytically.
24
        Args:
25
             a (float): Element at position (0,0).
```

```
26
           b (float): Element at position (0,1).
27
            c (float): Element at position (1,0).
28
            d (float): Element at position (1,1).
29
       Returns:
30
           Tuple[float, float]: The two eigenvalues of the matrix.
31
       Raises:
       11 11 11
32
33
       trace = a + d
35
       det = a * d - b * c
       discriminant = trace**2 - 4 * det
36
37
38
       #complex if discriminant negative
       discriminant root = np.sqrt(discriminant) if discriminant >= 0 else
39
       np.sqrt(complex(discriminant))
40
41
       lambda1 = (trace + discriminant_root) / 2
42
       lambda2 = (trace - discriminant_root) / 2
43
44
       return lambda1, lambda2
45
46
   def analyze_orthogonal_and_hessenberg(n=4, n_matrices=30):
47
48
49
       Analyzes orthogonal matrices and their Hessenberg forms.
50
       Args:
            n (int): Size of the matrices (n \times n).
51
52
            n_matrices (int): Number of orthogonal matrices to generate and analyze.
53
       Returns:
54
           None
55
       Raises:
56
           None
       11 11 11
57
58
59
        for i in range(n_matrices):
            print(f"\n--- Orthogonal Matrix Q number {i+1} ---")
60
61
            Q = generate orthogonal matrix gr(n=n)
            print("Matrix Q:")
62
            print(np.array_str(Q, precision=4, suppress_small=True))
63
64
65
            householder_list, H, Q_accum = to_hessenberg(Q)
66
67
            print("\nHessenberg Form H (of Q):")
68
            print(np.array_str(H, precision=4, suppress_small=True))
69
70
           block = Q[2:4, 2:4]
```

```
71
            a, b, c, d = block[0,0], block[0,1], block[1,0], block[1,1]
72
            analytical eigenvalues = analytical eigenvalues 2x2(a, b, c, d)
73
74
            print("\nBlock Q[3:4,3:4] (indices 2 and 3, 2x2):")
75
76
            print(np.array_str(block, precision=4, suppress_small=True))
77
78
            print("\nEigenvalues of the 2x2 block (analytically calculated):")
79
            for idx, val in enumerate(analytical_eigenvalues):
                 print(f" \lambda_{\text{idx+1}} = \{\text{val}\} \text{ (size = } \{\text{abs(val):.4f}\})")
80
81
82
            print("-" * 40)
83
84 analyze_orthogonal_and_hessenberg()
```

We ran this code for 30 matrices, the output was:

```
1
    --- Orthogonal Matrix Q number 1 ---
2
    Matrix Q:
3
   [[-0.5629 0.6801 0.4635 -0.0764]
     [-0.6703 -0.6884 0.2231 0.1645]
5
     [-0.1497 0.2337 -0.3793 0.8827]
6
     [ 0.4598 -0.0949  0.7691  0.4336]]
7
8
    Hessenberg Form H (of Q):
    [[-0.5629 -0.6779 -0.4534 -0.1342]
10
     [ 0.8265 -0.4617 -0.3088 -0.0914]
            -0.5721 0.7865 0.2329]
11
     [ 0.
12
     [-0.
               0. 0.2839 -0.9588]]
13
14
    Block Q[3:4,3:4] (indices 2 and 3, 2x2):
   [[-0.3793 0.8827]
15
16
    [ 0.7691  0.4336]]
17
    Eigenvalues of the 2x2 block (analytically calculated):
18
19
     \lambda 1 = 0.9458819605346136  (size = 0.9459)
20
     \lambda 2 = -0.8915812804514585  (size = 0.8916)
21
22
    --- Orthogonal Matrix Q number 2 ---
23
    Matrix Q:
24
    [[-0.4016 0.3605 0.8354 0.1045]
    [-0.2846 -0.3518 0.1255 -0.8829]
26
     [-0.3325 -0.8166 0.136
27
                               0.4519]
     [ 0.8045 -0.282    0.5176 -0.0734]]
28
29
    Hessenberg Form H (of Q):
```

```
[[-0.4016 -0.3235 -0.1952 0.8343]
32
    [ 0.9158 -0.1418 -0.0856  0.3658]
33
     [ 0. -0.9355 0.0805 -0.3439]
     [ 0. 0. -0.9737 -0.2278]]
34
35
    Block Q[3:4,3:4] (indices 2 and 3, 2x2):
37
   [[ 0.136  0.4519]
38
   [ 0.5176 -0.0734]]
39
40
   Eigenvalues of the 2x2 block (analytically calculated):
41
    \lambda_1 = 0.5261528266779573 (size = 0.5262)
42
     \lambda_2 = -0.4635182526918817 \text{ (size = 0.4635)}
43
   -----
44
45
   --- Orthogonal Matrix Q number 3 ---
    Matrix Q:
47
    [[-0.0452 -0.9852 -0.1571 0.0523]
    [ 0.4259  0.0412 -0.0809  0.9002]
48
49
   [ 0.1843  0.1346 -0.9569 -0.1793]
    [-0.8846 0.0982 -0.2303 0.3934]]
50
51
52
   Hessenberg Form H (of Q):
   [[-0.0452  0.4954  -0.8604  -0.1112]
53
54
   [-0.999 -0.0224 0.0389 0.005]
55
   [ 0. 0.8684 0.4918 0.0636]
              0. 0.1282 -0.9917]]
56
    [-0.
57
58
    Block Q[3:4,3:4] (indices 2 and 3, 2x2):
59
   [[-0.9569 -0.1793]
   [-0.2303 0.3934]]
60
61
62
   Eigenvalues of the 2x2 block (analytically calculated):
63
   \lambda_1 = 0.42331102317930497 (size = 0.4233)
64
     \lambda 2 = -0.9868680130188092 \text{ (size = 0.9869)}
65
66
67
   --- Orthogonal Matrix Q number 4 ---
    Matrix Q:
68
    [[-0.2568 0.8228 -0.2287 0.4525]
70
   [-0.2848 -0.018  0.9011  0.3265]
   [-0.6054 -0.5408 -0.3667 0.4544]
71
72
   [ 0.6975 -0.1738 -0.0346  0.6943]]
73
74 Hessenberg Form H (of Q):
75
    [[-0.2568 0.2274 0.1895 0.92 ]
76 [ 0.9665 0.0604 0.0503 0.2444]
```

```
[-0. -0.9719 0.0475 0.2305]
77
78
     [ 0. 0. -0.9794 0.2017]]
79
    Block Q[3:4,3:4] (indices 2 and 3, 2x2):
80
    [[-0.3667 0.4544]
81
    [-0.0346 0.6943]]
83
84
   Eigenvalues of the 2x2 block (analytically calculated):
   \lambda_1 = 0.67929095950588 (size = 0.6793)
85
86
     \lambda 2 = -0.3516952691053273 \text{ (size = 0.3517)}
87
88
89
   --- Orthogonal Matrix Q number 5 ---
    Matrix Q:
90
    [[-0.5025 -0.7649 -0.0345 0.4015]
91
    [ 0.3718  0.0654  0.6626  0.6469]
93
   [ 0.6819 -0.6372  0.0297 -0.358 ]
    [ 0.3798  0.0679 -0.7476  0.5406]]
94
95
96
   Hessenberg Form H (of Q):
97
   [[-0.5025 0.1798 -0.7903 0.3011]
98
   [-0.8646 -0.1045 0.4593 -0.175 ]
99 [-0. -0.9781 -0.1943 0.074 ]
100 [-0. 0. 0.356 0.9345]]
101
102 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
103 [[ 0.0297 -0.358 ]
104 [-0.7476 0.5406]]
105
106 Eigenvalues of the 2x2 block (analytically calculated):
107
      \lambda 1 = 0.8621172090206812 \text{ (size = 0.8621)}
108
    \lambda_2 = -0.2918043055687003 (size = 0.2918)
109 -----
110
111 --- Orthogonal Matrix Q number 6 ---
112 Matrix 0:
113 [[-0.9092 0.1745 0.2312 -0.2992]
114 [ 0.1618 -0.3496 -0.2497 -0.8884]
115 [-0.1454 0.4629 -0.8736 0.0369]
116 [-0.3551 -0.7956 -0.3479 0.3462]]
117
118 Hessenberg Form H (of Q):
119 [[-0.9092 -0.2422 -0.3011 -0.1552]
120 [-0.4164 0.5288 0.6573 0.3389]
121 [ 0.
              0.8134 -0.517 -0.2665]
              0. 0.4582 -0.8888]]
122 [-0.
```

```
123
124 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
125 [[-0.8736 0.0369]
126 [-0.3479 0.3462]]
127
128 Eigenvalues of the 2x2 block (analytically calculated):
129 \lambda_1 = 0.3356278613353456 (size = 0.3356)
130 \lambda 2 = -0.8630034423078552 (size = 0.8630)
131 -----
132
133 --- Orthogonal Matrix Q number 7 ---
134 Matrix Q:
135 [[-0.4296 0.6844 -0.4085 0.4245]
136 [ 0.2184 -0.4244 -0.028  0.8783]
137 [ 0.17 -0.3028 -0.9122 -0.2177]
138 [ 0.8596  0.5097 -0.0167  0.032 ]]
139
140 Hessenberg Form H (of Q):
141 [[-0.4296 -0.4928 0.7535 0.0703]
142 [-0.903 0.2344 -0.3584 -0.0334]
143 [-0. -0.838 -0.5433 -0.0507]
144 [ 0. 0. 0.0928 -0.9957]]
145
146 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
147 [[-0.9122 -0.2177]
148 [-0.0167 0.032]]
149
150 Eigenvalues of the 2x2 block (analytically calculated):
151 \lambda 1 = 0.0358294023777706 (size = 0.0358)
152
    \lambda_2 = -0.9159948591320213 (size = 0.9160)
153 -----
154
155 --- Orthogonal Matrix Q number 8 ---
156 Matrix 0:
157 [[-0.3402 -0.0284 -0.009
                            0.9399]
158 [-0.7148 -0.6207 0.1662 -0.2759]
159 [-0.5681 0.5973 -0.5323 -0.1927]
161
162 Hessenberg Form H (of Q):
163 [[-0.3402 0.2518 0.8476 0.3201]
164 [ 0.9403  0.0911  0.3067  0.1158]
165 [ 0. 0.9635 -0.2505 -0.0946]
           -0. 0.3533 -0.9355]]
166 [-0.
167
168 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
```

```
169 [[-0.5323 -0.1927]
170 [-0.83 0.0581]]
171
172 Eigenvalues of the 2x2 block (analytically calculated):
      \lambda 1 = 0.25997158900622225  (size = 0.2600)
173
    \lambda 2 = -0.7341829044352151 \text{ (size = 0.7342)}
175 -----
176
177 --- Orthogonal Matrix Q number 9 ---
178 Matrix Q:
179 [[-0.2692 0.5878 -0.5428 0.5361]
180 [-0.8282 0.0254 0.5486 0.1116]
181 [-0.292 0.3638 -0.2875 -0.8365]
182 [-0.3954 -0.7222 -0.5673 0.0189]]
183
184 Hessenberg Form H (of Q):
185 [[-0.2692 -0.561 -0.1619 0.7659]
186 [ 0.9631 -0.1568 -0.0453  0.2141]
187 [-0.
            -0.8128 0.1205 -0.5699]
188 [ 0. -0. -0.9784 -0.2069]]
189
190 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
191 [[-0.2875 -0.8365]
192 [-0.5673 0.0189]]
193
194 Eigenvalues of the 2x2 block (analytically calculated):
195 \lambda_1 = 0.5713848430035342 (size = 0.5714)
196 \lambda_2 = -0.8399942790872519 (size = 0.8400)
197 -----
198
199 --- Orthogonal Matrix Q number 10 ---
200 Matrix 0:
201 [[-0.4241 0.1349 -0.1773 0.8778]
202 [-0.332 -0.8664 -0.3594 -0.0999]
203 [ 0.8422 -0.2846 -0.2058  0.409 ]
204 [-0.0237 -0.3876 0.8928 0.2284]]
205
206 Hessenberg Form H (of Q):
207 [[-0.4241 -0.2373 0.8677 0.1046]
208 [ 0.9056 -0.1111  0.4063  0.049 ]
209 [-0. 0.9651 0.2602 0.0313]
210 [ 0.
              0. 0.1196 -0.9928]]
211
212 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
213 [[-0.2058 0.409]
214 [ 0.8928  0.2284]]
```

```
215
216 Eigenvalues of the 2x2 block (analytically calculated):
217 \lambda 1 = 0.6533894082311485 (size = 0.6534)
218 \lambda_2 = -0.6307995911677337 (size = 0.6308)
219 -----
220
221 --- Orthogonal Matrix Q number 11 ---
222 Matrix 0:
223 [[-0.1675 -0.9786 -0.0461 -0.1099]
224 [ 0.7871 -0.1742 0.5819 0.1072]
225 [ 0.3816 -0.1052 -0.6644 0.6339]
226 [-0.4547 -0.0293 0.4667 0.758]]
227
228 Hessenberg Form H (of Q):
229 [[-0.1675 0.7485 -0.1241 -0.6295]
230 [-0.9859 -0.1271 0.0211 0.1069]
231 [ 0. -0.6508 -0.1468 -0.7449]
232 [ 0.
            -0. -0.9811 0.1934]]
233
234 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
235 [[-0.6644 0.6339]
236 [ 0.4667 0.758 ]]
237
238 Eigenvalues of the 2x2 block (analytically calculated):
239
      \lambda_1 = 0.9421402114923986 (size = 0.9421)
240 \lambda 2 = -0.8485799008471894 (size = 0.8486)
241 -----
242
243 --- Orthogonal Matrix Q number 12 ---
244 Matrix Q:
245 [[-0.3541 0.5585 -0.0616 0.7476]
246 [-0.5108 -0.6958 -0.4435 0.2414]
247 [ 0.1705 0.3507 -0.885 -0.2542]
248 [ 0.7646 -0.2844 -0.1274 0.5641]]
249
250 Hessenberg Form H (of Q):
251 [[-0.3541 0.295 0.7613 0.4561]
252 [ 0.9352  0.1117  0.2883  0.1727]
           0.949 -0.2706 -0.1621]
253 [-0.
254 [-0. -0. 0.5139 -0.8579]]
255
256 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
257 [[-0.885 -0.2542]
258 [-0.1274 0.5641]]
259
260 Eigenvalues of the 2x2 block (analytically calculated):
```

```
261
    \lambda_1 = 0.5861402323977607 (size = 0.5861)
262
      \lambda 2 = -0.9070552039589896  (size = 0.9071)
263 -----
264
265 --- Orthogonal Matrix Q number 13 ---
266 Matrix Q:
267 [[-0.7015  0.4915  0.3042 -0.417 ]
268 [ 0.4623 -0.1626  0.1522 -0.8583]
269 [ 0.2479  0.6778 -0.6824 -0.1159]
270 [-0.4825 -0.5221 -0.647 -0.2757]]
271
272 Hessenberg Form H (of Q):
273 [[-0.7015 -0.7069 -0.0829 -0.0373]
274 [-0.7127 0.6958 0.0816 0.0367]
275 [ 0. 0.1276 -0.9045 -0.4069]
276 [ 0. -0. 0.4103 -0.912 ]]
277
278 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
279 [[-0.6824 -0.1159]
280 [-0.647 -0.2757]]
281
282 Eigenvalues of the 2x2 block (analytically calculated):
283 \lambda 1 = -0.1379150700589457 (size = 0.1379)
284
     \lambda 2 = -0.820164584090632 \text{ (size = 0.8202)}
285 -----
286
287 --- Orthogonal Matrix Q number 14 ---
288 Matrix Q:
289 [[-0.2164 -0.5735 0.7758 -0.1498]
290 [-0.3581 -0.6722 -0.6278 -0.1609]
291 [-0.1535 0.3054 0.0015 -0.9398]
292 [-0.8952 0.3551 0.0633 0.2617]]
293
294 Hessenberg Form H (of Q):
295 [[-0.2164 0.2256 -0.3541 0.8814]
296 [ 0.9763  0.05  -0.0785  0.1954]
297 [-0. -0.9729 -0.0862 0.2144]
            0. -0.9279 -0.3728]]
298 [-0.
299
300 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
301 [[ 0.0015 -0.9398]
302 [ 0.0633  0.2617]]
303
304 Eigenvalues of the 2x2 block (analytically calculated):
      \lambda_1 = (0.1316169167334142 + 0.20628124638940884j) (size = 0.2447)
305
306
      \lambda_2 = (0.1316169167334142 - 0.20628124638940884j) (size = 0.2447)
```

```
308
309 --- Orthogonal Matrix Q number 15 ---
310 Matrix Q:
311 [[-0.467  0.1387  0.7316  0.4769]
312 [ 0.0375 -0.9757  0.0774  0.2017]
313 [-0.7384 -0.0272 -0.627 0.2467]
314 [ 0.485  0.1677 -0.2562  0.8191]]
315
316 Hessenberg Form H (of Q):
317 [[-0.467  0.3435 -0.8022 -0.1428]
318 [-0.8843 -0.1814 0.4236 0.0754]
319 [-0. 0.9215 0.3824 0.068 ]
320 [-0. -0. 0.1752 -0.9845]]
321
322 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
323 [[-0.627 0.2467]
324 [-0.2562 0.8191]]
325
326 Eigenvalues of the 2x2 block (analytically calculated):
327
    \lambda 1 = 0.7740235941481243 (size = 0.7740)
328 \lambda_2 = -0.5818796203145907 (size = 0.5819)
329 -----
330
331 --- Orthogonal Matrix Q number 16 ---
332 Matrix 0:
333 [[-0.3849 0.0435 -0.7406 0.549]
334 [ 0.2525 -0.952 -0.07  0.158 ]
335 [ 0.7807  0.2969  0.0191  0.5495]
336 [-0.4225 -0.06  0.668  0.6096]]
337
338 Hessenberg Form H (of Q):
339 [[-0.3849 0.866 0.1952 0.2527]
340 [-0.923 -0.3611 -0.0814 -0.1054]
341 [ 0. 0.346 -0.5736 -0.7425]
342 [ 0. 0. -0.7914 0.6114]]
343
344 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
345 [[0.0191 0.5495]
346 [0.668 0.6096]]
347
348 Eigenvalues of the 2x2 block (analytically calculated):
\lambda_1 = 0.9883202000131572  (size = 0.9883)
     \lambda 2 = -0.3596282457787697 \text{ (size = 0.3596)}
350
351 -----
352
```

```
353 --- Orthogonal Matrix Q number 17 ---
354 Matrix Q:
355 [[-0.1066 0.7212 0.0749 -0.6804]
356 [-0.6764 -0.5121 0.3485 -0.3985]
357 [-0.5738 0.1159 -0.8012 0.1245]
358 [-0.4493 0.4519 0.4807 0.6024]]
359
360 Hessenberg Form H (of Q):
361 [[-0.1066 -0.2265 -0.8608 -0.4431]
362 [ 0.9943 -0.0243 -0.0923 -0.0475]
363 [ 0. -0.9737 0.2025 0.1043]
364 [ 0.
           0. 0.4577 -0.8891]]
365
366 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
367 [[-0.8012 0.1245]
368 [ 0.4807  0.6024]]
369
370 Eigenvalues of the 2x2 block (analytically calculated):
371 \lambda 1 = 0.6437814804055579 (size = 0.6438)
\lambda_2 = -0.842579679233141 \text{ (size = 0.8426)}
373 -----
374
375 --- Orthogonal Matrix Q number 18 ---
376 Matrix 0:
377 [[-0.8255 0.1636 0.5347 0.0763]
378 [-0.5177 -0.2699 -0.6467 -0.4908]
379 [ 0.0194  0.9433  -0.2236  -0.2446]
380 [-0.2238 0.103 -0.4958 0.8327]]
381
382 Hessenberg Form H (of Q):
383 [[-0.8255 -0.1619 -0.4367 -0.3188]
384 [ 0.5644 -0.2368 -0.6388 -0.4663]
385 [ 0. 0.958 -0.2317 -0.1691]
              0. -0.5896 0.807711
386 [-0.
387
388 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
389 [[-0.2236 -0.2446]
390 [-0.4958 0.8327]]
391
392 Eigenvalues of the 2x2 block (analytically calculated):
     \lambda 1 = 0.9372008193289816  (size = 0.9372)
393
394 \lambda 2 = -0.32809878403400955 (size = 0.3281)
395 -----
396
397 --- Orthogonal Matrix Q number 19 ---
398 Matrix Q:
```

```
399 [[-0.7885 0.0127 0.4922 -0.3686]
400 [ 0.5982 -0.2155  0.6311 -0.4444]
401 [ 0.0328  0.1282 -0.5621 -0.8164]
402 [-0.1391 -0.968 -0.2085 -0.0141]]
403
404 Hessenberg Form H (of Q):
405 [[-0.7885 -0.122 -0.4769 0.3687]
406 [-0.615 0.1564 0.6114 -0.4727]
407 [ 0. 0.9801 -0.1569 0.1213]
408 [ 0.
              0. -0.6116 -0.7911]]
409
410 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
411 [[-0.5621 -0.8164]
412 [-0.2085 -0.0141]]
413
414 Eigenvalues of the 2x2 block (analytically calculated):
415 \lambda_1 = 0.2071704757269035 (size = 0.2072)
    \lambda 2 = -0.7833862909149965  (size = 0.7834)
416
417 -----
418
419 --- Orthogonal Matrix Q number 20 ---
420 Matrix Q:
421 [[-0.3031 0.0429 0.9481 0.0861]
422 [ 0.1571 -0.9342 0.1195 -0.2972]
423 [-0.8533 -0.0239 -0.2292 -0.4678]
424 [-0.3942 -0.3534 -0.1853 0.8279]]
425
426 Hessenberg Form H (of Q):
427 [[-0.3031 0.8775 -0.2647 0.261]
428 [-0.953 -0.2791 0.0842 -0.083]
429 [ 0. 0.3901 0.6557 -0.6464]
430 [ 0. -0. -0.702 -0.7121]]
431
432 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
433 [[-0.2292 -0.4678]
434 [-0.1853 0.8279]]
435
436 Eigenvalues of the 2x2 block (analytically calculated):
437 \lambda 1 = 0.9043475415351031 (size = 0.9043)
438
    \lambda_2 = -0.30565758703551016 (size = 0.3057)
439 -----
440
441 --- Orthogonal Matrix Q number 21 ---
442 Matrix Q:
443 [[-0.8149 0.3649 -0.4406 -0.0928]
444 [ 0.0977 -0.6065 -0.7405 0.2726]
```

```
445 [ 0.0387  0.372  0.0415  0.9265]
446 [-0.57 -0.6005 0.5058 0.2423]]
447
448 Hessenberg Form H (of Q):
449 [[-0.8149 -0.1234 0.2317 0.5167]
450 [-0.5796 0.1735 -0.3257 -0.7266]
451 [ 0. -0.9771 -0.0871 -0.1943]
452 [-0. 0. 0.9125 -0.4091]]
453
454 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
455 [[0.0415 0.9265]
456
    [0.5058 0.2423]]
457
458 Eigenvalues of the 2x2 block (analytically calculated):
459 \lambda 1 = 0.8337542266557703 (size = 0.8338)
460
    \lambda 2 = -0.5499977130761522  (size = 0.5500)
461 -----
462
463 --- Orthogonal Matrix Q number 22 ---
464 Matrix Q:
465 [[-0.3663 0.4189 -0.6842 -0.4714]
466 [ 0.2919 -0.672 -0.6656 0.142 ]
467 [ 0.5024  0.6076 -0.2758  0.5498]
468 [-0.7268 -0.061 -0.1131 0.6748]]
469
470 Hessenberg Form H (of Q):
471 [[-0.3663 -0.1301 0.2621 0.8833]
472 [-0.9305 0.0512 -0.1032 -0.3477]
473 [-0. -0.9902 -0.0398 -0.134 ]
474 [ 0. -0. 0.9587 -0.2845]]
475
476 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
477 [[-0.2758 0.5498]
478 [-0.1131 0.6748]]
479
480 Eigenvalues of the 2x2 block (analytically calculated):
481
    \lambda_1 = 0.6040601009013424 (size = 0.6041)
482
    \lambda_2 = -0.20508048336653284 (size = 0.2051)
483 ------
484
485 --- Orthogonal Matrix Q number 23 ---
486 Matrix 0:
487 [[-0.4467 -0.7825 -0.2287 0.3687]
488 [ 0.4222 0.182 -0.0157 0.8879]
489 [ 0.6922 -0.3543 -0.5694 -0.2666]
490 [-0.3783 0.4786 -0.7895 0.0678]]
```

```
491
492 Hessenberg Form H (of Q):
493 [[-0.4467 0.702 -0.0795 -0.5489]
494 [-0.8947 -0.3505 0.0397 0.274]
495 [ 0. -0.62 -0.1125 -0.7765]
496 [ 0. 0. -0.9897 0.1433]]
497
498 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
499 [[-0.5694 -0.2666]
500 [-0.7895 0.0678]]
501
502 Eigenvalues of the 2x2 block (analytically calculated):
      \lambda 1 = 0.3077269347022792  (size = 0.3077)
504
    \lambda 2 = -0.8093108181365211  (size = 0.8093)
505 -----
506
507 --- Orthogonal Matrix Q number 24 ---
508 Matrix 0:
509 [[-0.0413 -0.9591 0.2707 0.0721]
510 [ 0.08 -0.274 -0.9584 0.0005]
511 [-0.6777 -0.0389 -0.0459 -0.7328]
512 [-0.7298 0.0604 -0.0778 0.6766]]
513
514 Hessenberg Form H (of Q):
515 [[-0.0413  0.3131  0.5108 -0.7996]
516 [-0.9991 -0.0129 -0.0211 0.0331]
517 [-0. 0.9496 -0.1687 0.2641]
518 [ 0. 0. 0.8427 0.5384]]
519
520 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
521 [[-0.0459 -0.7328]
522 [-0.0778 0.6766]]
523
524 Eigenvalues of the 2x2 block (analytically calculated):
525 \lambda_1 = 0.7483535886136121 (size = 0.7484)
526
    \lambda 2 = -0.1176716985715956 (size = 0.1177)
527 -----
528
529 --- Orthogonal Matrix Q number 25 ---
530 Matrix Q:
531 [[-0.7483 0.5153 -0.0763 0.4107]
532 [-0.4762 -0.7375 -0.4779 -0.0313]
533 [-0.1713 0.3719 -0.3481 -0.8433]
534 [ 0.4288  0.2287 -0.8029  0.3451]]
535
536 Hessenberg Form H (of Q):
```

```
537 [[-0.7483 -0.0847 0.4863 0.4431]
538 [ 0.6633 -0.0956  0.5486  0.4998]
              0.9918 0.0944 0.086 ]
539 [ 0.
              0. 0.6735 -0.7392]]
540 [ 0.
541
542 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
543 [[-0.3481 -0.8433]
544 [-0.8029 0.3451]]
545
546 Eigenvalues of the 2x2 block (analytically calculated):
547
      \lambda 1 = 0.8914410770554546 (size = 0.8914)
    \lambda_2 = -0.8943450015206609 (size = 0.8943)
548
549 -----
550
551 --- Orthogonal Matrix Q number 26 ---
552 Matrix Q:
553 [[-0.9036 0.127 -0.0161 0.4088]
554 [-0.2097 -0.5366 -0.7493 -0.3265]
555 [ 0.3449  0.3256 -0.6074  0.6373]
556 [ 0.1433 -0.7681 0.2634 0.5658]]
557
558 Hessenberg Form H (of Q):
559 [[-0.9036 0.0616 0.2624 0.3329]
560 [ 0.4284 0.13 0.5536 0.7022]
561 [ 0. 0.9896 -0.0891 -0.113 ]
562
    [-0. -0. 0.7853 -0.6191]]
563
564 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
565 [[-0.6074 0.6373]
566 [ 0.2634 0.5658]]
567
568 Eigenvalues of the 2x2 block (analytically calculated):
\lambda_1 = 0.6947481590186378 (size = 0.6947)
570
     \lambda 2 = -0.7362843808778513 (size = 0.7363)
571 -----
572
573 --- Orthogonal Matrix Q number 27 ---
574 Matrix Q:
575 [[-0.3783 0.2175 0.7347 -0.5194]
576 [-0.486 -0.5305 -0.4607 -0.5198]
577 [-0.7609 0.4199 -0.1943 0.455]
578 [-0.2046 -0.7036 0.4585 0.5029]]
579
580 Hessenberg Form H (of Q):
581 [[-0.3783 -0.6032 -0.0497 -0.7004]
582 [ 0.9257 -0.2465 -0.0203 -0.2862]
```

```
583 [ 0. 0.7585 -0.0461 -0.65 ]
584 [ 0. -0. -0.9975 0.0708]]
585
586 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
587 [[-0.1943 0.455]
588
    [ 0.4585 0.5029]]
589
590 Eigenvalues of the 2x2 block (analytically calculated):
591 \lambda 1 = 0.7288996874702811 (size = 0.7289)
592
    \lambda 2 = -0.42026844598624513 (size = 0.4203)
593 -----
594
595 --- Orthogonal Matrix Q number 28 ---
596 Matrix Q:
597 [[-0.6177 -0.2663 -0.3252 0.6646]
598 [ 0.7345 -0.3401  0.0741  0.5826]
599 [ 0.0015 -0.8476 -0.2571 -0.4641]
600 [ 0.2811 0.308 -0.907 -0.0592]]
601
602 Hessenberg Form H (of Q):
603 [[-0.6177 0.0118 0.5166 0.5928]
604 [-0.7864 -0.0093 -0.4058 -0.4656]
605 [ 0. -0.9999 0.0099 0.0113]
606 [ 0.
           -0. 0.7539 -0.657 ]]
607
608 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
609 [[-0.2571 -0.4641]
610 [-0.907 -0.0592]]
611
612 Eigenvalues of the 2x2 block (analytically calculated):
613
     \lambda 1 = 0.4981407629675436  (size = 0.4981)
614
    \lambda_2 = -0.8144343078024388 (size = 0.8144)
615 -----
616
617 --- Orthogonal Matrix Q number 29 ---
618 Matrix 0:
619 [[-0.889 -0.0288 0.3962 -0.2278]
620 [ 0.1961 -0.4549 -0.0899 -0.864 ]
621 [-0.4017 -0.36 -0.8217 0.1838]
622 [ 0.0995 -0.814  0.3997  0.4095]]
623
624 Hessenberg Form H (of Q):
625 [[-0.889  0.4094  0.14  -0.1501]
626 [-0.458 -0.7947 -0.2718 0.2914]
627 [ 0. -0.4483 0.6097 -0.6537]
628 [ 0. -0. -0.7313 -0.6821]]
```

```
629
630 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
631 [[-0.8217 0.1838]
632 [ 0.3997 0.4095]]
633
634 Eigenvalues of the 2x2 block (analytically calculated):
     \lambda_1 = 0.46657705244665193 (size = 0.4666)
636
      \lambda 2 = -0.8787442629640516  (size = 0.8787)
637 -----
638
639 --- Orthogonal Matrix Q number 30 ---
640 Matrix Q:
641 [[-0.2493 0.2801 -0.5896 -0.7154]
642 [-0.5128 -0.2897 0.6545 -0.4742]
643 [-0.2303 -0.8469 -0.4616 0.1292]
644 [-0.7886 0.3471 -0.1044 0.4967]]
645
646 Hessenberg Form H (of Q):
647 [[-0.2493 0.5744 -0.1969 -0.7544]
648 [ 0.9684  0.1479  -0.0507  -0.1942]
649 [ 0. -0.8051 -0.1498 -0.5739]
650 [ 0. -0.
                 0.9676 -0.2526]]
651
652 Block Q[3:4,3:4] (indices 2 and 3, 2x2):
653 [[-0.4616 0.1292]
654 [-0.1044 0.4967]]
655
656 Eigenvalues of the 2x2 block (analytically calculated):
     \lambda 1 = 0.4824356418279282  (size = 0.4824)
658
      \lambda_2 = -0.4473584670796439 (size = 0.4474)
659 -----
```

So we observe that in the 2×2 blocks analyzed:

- 1. Orthogonality is not always preserved
- 2. The eigenvalues are usually real, with alternating sign and size around 1.

4.5. Shift With an Eigenvalue (d)

Now we use an eigenvalue of the 2×2 block as a shift:

```
1  def qr_iteration_with_fixed_shift(H, mu, max_iter=100):
2
3    """
4    Applies QR iteration with fixed shift on a matrix H.
5
6    Args:
7    H (np.ndarray): initial matrix in Hessenberg form.
```

```
8
            mu (complex): fixed shift to be used.
9
            max iter (int): maximum number of iterations.
10
11
        Returns:
12
            Hk (np.ndarray): matrix after iterations.
13
            converged (bool): whether it converged to almost upper triangular form.
        11 11 11
14
15
16
        Hk = H.copy()
17
        n = Hk.shape[0]
18
19
        for _ in range(max_iter):
20
            H 	ext{ shifted} = Hk - mu * np.eye(n)
            Q, R = np.linalg.qr(H_shifted)
22
            Hk = R @ Q + mu * np.eye(n)
23
24
        subdiag = np.abs(np.diag(Hk, k=-1))
25
        tol = 1e-5
26
        converged = np.all(subdiag < tol)</pre>
27
        return Hk, converged
28
29 def run_qr_iteration_with_shifts(n=4, n_matrices=30):
30
        Runs QR iteration with fixed shift on randomly generated orthogonal
32
        matrices.
33
34
        Args:
            n (int): Size of the matrices (n \times n).
35
36
            n_matrices (int): Number of orthogonal matrices to generate and analyze.
37
38
        Returns:
39
            None
40
41
        Raises:
42
            None
        11 11 11
43
44
        for i in range(n_matrices):
45
            print(f"\n--- Orthogonal Matrix Q number {i+1} ---")
46
47
            Q = generate_orthogonal_matrix_qr(n=n)
48
            _, H, _ = to_hessenberg(Q)
49
50
            final_block = H[-2:, -2:]
            a, b, c, d = final_block[0,0], final_block[0,1], final_block[1,0],
51
            final_block[1,1]
```

```
52
           shift_candidates = analytical_eigenvalues_2x2(a, b, c, d)
53
54
           mu = shift candidates[0] #use the first eigenvalue as fixed shift
           print(f"Fixed shift used (eigenvalue of the final block): {mu} (modulus
55
           {abs(mu):.4f})")
56
57
           Hk, converged = qr_iteration_with_fixed_shift(H, mu, max_iter=20)
58
           print("Matrix after 20 QR iterations with fixed shift (values below the
59
           subdiagonal):")
           print(np.array str(np.diag(Hk, k=-1), precision=3, suppress small=True))
60
61
           print(f"Converged to almost upper triangular form? {'Yes' if converged
62
           else 'No'}")
           print("-" * 50)
63
64
65
66 run qr iteration with shifts()
```

We once more ran this on 30 random matrices, with 100 iterations and using a generous tolarance = 1e-5 for convergence. The output is:

```
1
    --- Orthogonal Matrix Q number 1 ---
    Fixed shift used (eigenvalue of the final block): 0.45675480266096846 (modulus
2
    0.4568)
    Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
3
    [-0.006 1.
                   0.
5
    Converged to almost upper triangular form? No
6
8
    --- Orthogonal Matrix Q number 2 ---
    Fixed shift used (eigenvalue of the final block): 0.47119769752489193 (modulus
    0.4712)
10
    Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
    [-0.443 0.501 -0.
    Converged to almost upper triangular form? No
12
13
    .....
14
15
    --- Orthogonal Matrix Q number 3 ---
    Fixed shift used (eigenvalue of the final block): 0.6543379277197392 (modulus
16
    0.6543)
17
    Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
18
    [-0.004 - 1.
                   0.
                        1
19
    Converged to almost upper triangular form? No
20
21
22
    --- Orthogonal Matrix Q number 4 ---
```

```
Fixed shift used (eigenvalue of the final block): 0.47308128373683983 (modulus
23
    0.4731)
24
    Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
25
    [ 0.47 -0.739 0. ]
    Converged to almost upper triangular form? No
26
    -----
28
29
    --- Orthogonal Matrix Q number 5 ---
    Fixed shift used (eigenvalue of the final block): 0.999835862374747 (modulus
30
    0.9998)
    Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
32
    [ 0.079 -0.95 -0.
                      1
33
    Converged to almost upper triangular form? No
34
    -----
35
   --- Orthogonal Matrix Q number 6 ---
    Fixed shift used (eigenvalue of the final block): 0.8163222681328892 (modulus
37
38
   Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
39
    [-0.597 -0.815 -0.
    Converged to almost upper triangular form? No
41
    -----
42
   --- Orthogonal Matrix Q number 7 ---
43
    Fixed shift used (eigenvalue of the final block): 0.8964184377049635 (modulus
44
    0.8964)
   Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
45
    [-0.37 -0.249 -0.
46
47
    Converged to almost upper triangular form? No
48
    ______
49
   --- Orthogonal Matrix Q number 8 ---
50
    Fixed shift used (eigenvalue of the final block): 0.9689586976565394 (modulus
51
    0.9690)
52
   Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
    [-0.204 -0.864 0.
                      ]
    Converged to almost upper triangular form? No
54
55
56
    --- Orthogonal Matrix Q number 9 ---
57
    Fixed shift used (eigenvalue of the final block): 0.8100766994771901 (modulus
58
    0.8101)
59
    Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
60
    [0.332 0.362 0.
                   1
61
    Converged to almost upper triangular form? No
62
    _____
63
```

```
--- Orthogonal Matrix Q number 10 ---
    Fixed shift used (eigenvalue of the final block):
65
    (-0.37373545734503094+0.5961171763741568j) (modulus 0.7036)
66
   Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
67
    [-0.817-0.j 0. -0.j -0.
                              -0.j]
    Converged to almost upper triangular form? No
    -----
69
70
   --- Orthogonal Matrix Q number 11 ---
    Fixed shift used (eigenvalue of the final block): 0.9508997822578601 (modulus
72
    Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
73
74
    [-0. -0.985 -0.
    Converged to almost upper triangular form? No
    _____
76
77
78
    --- Orthogonal Matrix Q number 12 ---
    Fixed shift used (eigenvalue of the final block): 0.49537543518658966 (modulus
79
    0.4954)
   Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
80
    [ 0.096  0.822 -0. ]
    Converged to almost upper triangular form? No
82
    .....
83
84
85
    --- Orthogonal Matrix Q number 13 ---
    Fixed shift used (eigenvalue of the final block): -0.5169109822890083 (modulus
    0.5169)
    Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
           0.57 0. ]
89
    Converged to almost upper triangular form? No
90
          91
92
    --- Orthogonal Matrix Q number 14 ---
    Fixed shift used (eigenvalue of the final block): 0.8706109171378603 (modulus
93
    0.8706)
   Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
    [-0.239 -0.766 0.
95
    Converged to almost upper triangular form? No
98
   --- Orthogonal Matrix Q number 15 ---
    Fixed shift used (eigenvalue of the final block): 0.7877591057872764 (modulus
100
    0.7878)
101 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
102 [-0.259 -0.103 -0.
                       1
103 Converged to almost upper triangular form? No
```

```
105
106 --- Orthogonal Matrix Q number 16 ---
Fixed shift used (eigenvalue of the final block): 0.7525805488977373 (modulus
    0.7526)
108 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
109 [-0.537 -0.738 -0.
                       1
110 Converged to almost upper triangular form? No
111 -----
112
113 --- Orthogonal Matrix Q number 17 ---
    Fixed shift used (eigenvalue of the final block): 0.9376989809342731 (modulus
    0.9377)
115 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
116 [ 0.003 -0.996 0.
                      -1
117 Converged to almost upper triangular form? No
119
120 --- Orthogonal Matrix Q number 18 ---
    Fixed shift used (eigenvalue of the final block):
    (-0.3332517830071887+0.31982101244995226j) (modulus 0.4619)
122 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
123 [-0.081+0.j 0. -0.j 0.003-0.j]
124 Converged to almost upper triangular form? No
125 -----
126
127 --- Orthogonal Matrix Q number 19 ---
    Fixed shift used (eigenvalue of the final block): -0.09828756789250936 (modulus
128
   0.0983)
129 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
130 [0.171 0.5
              0.14 ]
131 Converged to almost upper triangular form? No
132 -----
133
134 --- Orthogonal Matrix O number 20 ---
    Fixed shift used (eigenvalue of the final block): 0.9649949076474909 (modulus
135
    0.9650)
136 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
137 [ 0.014 -1. -0. ]
138 Converged to almost upper triangular form? No
139 -----
140
141 --- Orthogonal Matrix Q number 21 ---
    Fixed shift used (eigenvalue of the final block): 0.9511618027193621 (modulus
    0.9512)
143 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
144 [-0.435 0.573 0.
145 Converged to almost upper triangular form? No
```

```
147
148 --- Orthogonal Matrix Q number 22 ---
    Fixed shift used (eigenvalue of the final block): 0.8791066383784223 (modulus
    0.8791)
150 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
151 [-0.001 -0.998 -0.
152 Converged to almost upper triangular form? No
153 -----
154
155 --- Orthogonal Matrix O number 23 ---
    Fixed shift used (eigenvalue of the final block): 0.9726088054062819 (modulus
156
    0.9726)
157 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
158 [ 0.008 0.994 -0.
159 Converged to almost upper triangular form? No
160 -----
161
162 --- Orthogonal Matrix Q number 24 ---
    Fixed shift used (eigenvalue of the final block):
    (-0.48219741339866473+0.8310922170834656j) (modulus 0.9608)
164 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
165 [-0.442+0.j -0.
                    +0.j 0.
166 Converged to almost upper triangular form? No
167 -----
168
169 --- Orthogonal Matrix Q number 25 ---
    Fixed shift used (eigenvalue of the final block):
    (-0.9055728105908702+0.3001257739418847j) (modulus 0.9540)
171 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
172 [-0.+0.j -0.+0.j -0.-0.j]
173 Converged to almost upper triangular form? Yes
174 -----
175
176 --- Orthogonal Matrix Q number 26 ---
    Fixed shift used (eigenvalue of the final block): 0.9549576704039157 (modulus
177
    0.9550)
178 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
179 [ 0.001 0.995 -0.
                      - 1
180 Converged to almost upper triangular form? No
181 -----
182
183 --- Orthogonal Matrix Q number 27 ---
   Fixed shift used (eigenvalue of the final block): -0.3999018693674167 (modulus
    0.3999)
185 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
186 [0.
        0.693 0.001]
```

```
187 Converged to almost upper triangular form? No
188 -----
189
190 --- Orthogonal Matrix Q number 28 ---
   Fixed shift used (eigenvalue of the final block): 0.4453295247750607 (modulus
191
   0.4453)
192 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
193 [ 0.287 0.893 -0.
194 Converged to almost upper triangular form? No
195 -----
196
197 --- Orthogonal Matrix Q number 29 ---
   Fixed shift used (eigenvalue of the final block): 0.9851064687720523 (modulus
   0.9851)
199 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
200 [-0.002 1.
                -0.
201 Converged to almost upper triangular form? No
202 -----
203
204 --- Orthogonal Matrix Q number 30 ---
   Fixed shift used (eigenvalue of the final block): 0.9234616212297447 (modulus
205
   0.9235)
206 Matrix after 20 QR iterations with fixed shift (values below the subdiagonal):
207 [0.397 0.598 0. ]
208 Converged to almost upper triangular form? No
209 -----
```

We therefore conclude that:

- 1. There is usually no convergence to an upper triangular form, even after 100 iterations (we have seen only one case where it converged, with a generous tolerance of 10^{-5}).
- 2. Some values below the subdiagonal are still big (of order 0,01 and so).
- 3. The chosen shift was not enough for convergence

Bibliography

[1] L. N. Trefethen and D. Bau, Numerical Linear Algebra. 1997.