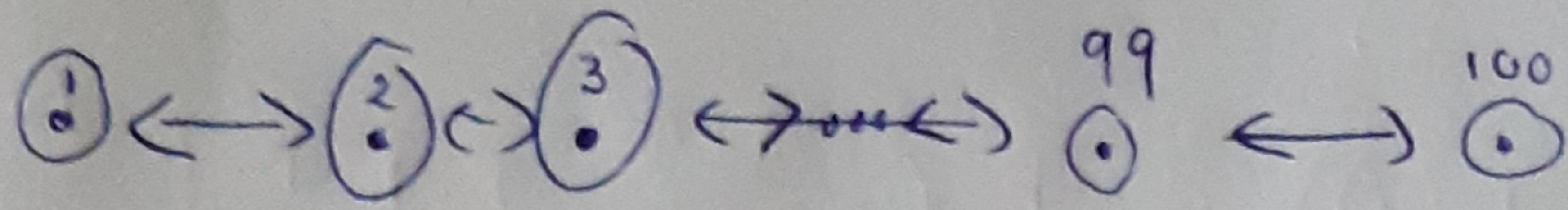


Exc 1

$$A = \begin{bmatrix} -1 & 101 & & & & \\ -99 & -2 & 101 & & & \\ & -99 & -2 & 101 & & \\ & & & \ddots & \ddots & \\ & & & & -99 & -2 & 101 \\ & & & & & -99 & -2 \end{bmatrix}$$

→ Show A irreducible graph of A:



graph strongly connected

all nodes are connected to each other, path from node i to j and vice versa for all i and j

⇒ A irreducible

b

$$A = \begin{bmatrix} -1 & 1 & & & & \\ 1 & -2 & 1 & & & \\ & & \ddots & \ddots & & \\ & & & -2 & 1 & \\ & & & & 1 & -2 \end{bmatrix} + \begin{bmatrix} 0 & 100 & & & & \\ -100 & 0 & 100 & & & \\ & & \ddots & \ddots & & \\ & & & -100 & 0 & 100 \\ & & & & -100 & 0 \end{bmatrix}$$

$$A = \frac{A^T + A}{2} + \frac{A^T - A}{2}$$

(any other splitting in symm. and skew symm is fine as well)

symmetric A_1

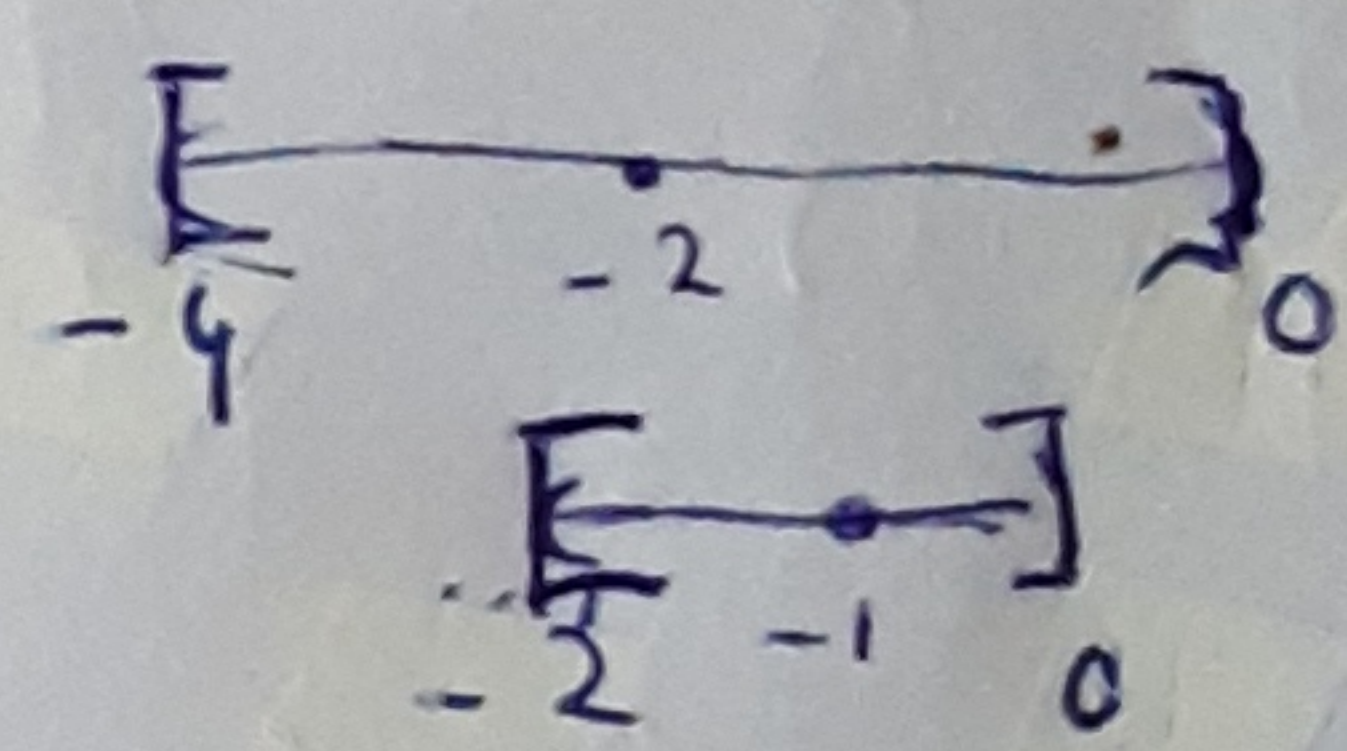
skew-symmetric A_2

0.1 A_1 symmetric ⇒ $\lambda \in \sigma(A)$ real
 A_1 irreducible

Gerschgorin on A_1 :

'circles' $|z+2| \leq 2: -4 \leq z \leq 0$

real intervals $|z+1| \leq 1: -2 \leq z \leq 0$



$$\cup \text{'circles'} = [-4, 0]$$

since A_1 irreducible, boundary not included, since boundary not on every 'circle' (Third Gerschgorin th.)

looking at columns gives similar result, since $A_1 = A_1^T$

$$\Rightarrow \sigma(A_1) \subset (-4, 0)$$

0.1 A_2 skew-symmetric ⇒ $\lambda \in \sigma(A_2)$ pure imaginary
 A_2 irreducible

$$\Rightarrow \text{circles } |z| \leq 100 \quad -100i \leq z \leq 100i \quad \cup \text{circles } = [-200i, 200i]$$

$$\text{intervals } |z| \leq 200 \quad -200i \leq z \leq 200i$$

A_2 irreducible, boundary not included, since boundary not on every circle

$$\Rightarrow \sigma(A_2) \subset (-200i, 200i)$$

c. field of values $F(A) = \left\{ \frac{(x, Ax)}{(x, x)} \mid x \in \mathbb{C}^n, x \neq 0 \right\}$

• $\sigma(A) \subset F(A)$

• A normal, i.e. $AA^T = A^T A \Rightarrow F(A) = \text{convex hull of } \sigma(A)$
(if A real)

0.2

• Berderson: $F(A) \subset F\left(\frac{A+A^T}{2}\right) + F\left(\frac{A-A^T}{2}\right)$

$\Rightarrow \sigma(A) \subset F(A) \subset F\left(\frac{A+A^T}{2}\right) + F\left(\frac{A-A^T}{2}\right)$

$= \left\{ x+iy \mid x \in (0,4), y \in (-200i, 200i) \right\}$

0.3

$\frac{A+A^T}{2}$ is normal because symm. $\Rightarrow F\left(\frac{A+A^T}{2}\right) = \text{convex hull of } \sigma\left(\frac{A+A^T}{2}\right) = (0,4)$

$\frac{A-A^T}{2}$ is normal because skew symm. $\Rightarrow F\left(\frac{A-A^T}{2}\right) = \text{convex hull of } \sigma\left(\frac{A-A^T}{2}\right) = (-200i, 200i)$

Exc 2.

a. • $A^{(0)} = A$

QR method

0.4

$\left. \begin{aligned} Q^{(i)} R^{(i)} &= A^{(i)} \\ A^{(i+1)} &= R^{(i)} Q^{(i)} \end{aligned} \right\} i = 0, 1, 2, \dots$

0.1

• $A^{(i)} \rightarrow$ upper triangular matrix for $i \rightarrow \infty$

• the eigenvalues on the diagonal of the converged $A^{(i)}$

0.2

are ordered from large to small in absolute value

• the convergence of element a_{kk} wrt. $a_{k-1, k-1}$

depends on $\left| \frac{\lambda_k}{\lambda_{k-1}} \right|$

0.2

assuming $|\lambda_1| > |\lambda_2| > |\lambda_3| > \dots > |\lambda_{n-1}| > |\lambda_n|$

b QR with shift

take shift s_i
in general $s_i = a_{nn}^{(i)}$

\Rightarrow in step i : use $A^{(i)} - s_i I$ instead of $A^{(i)}$

0.4 which has eigenvalues $\lambda_k - s_i$ $k = 1, \dots, n$

convergence speed in that step:

- order $|\lambda_k - s_i|$ from large to small, calling them μ_1, \dots, μ_n , then $|\mu_1| > |\mu_2| > \dots > |\mu_n|$

0.6 convergence for lower diagonal element; i.e. $(A^{(i)} - s_i I)_{nn}$

$$\left| \frac{\mu_n}{\mu_{n-1}} \right|$$

once $A_{nn}^{(i)}$ converges to an eigenvalue, μ_n will become smaller and hence convergence gets fast, it becomes faster in each step

c determine Householder matrix H , s.t. $H \begin{pmatrix} 1 \\ -\sqrt{3} \end{pmatrix} = \begin{pmatrix} * \\ 0 \end{pmatrix}$

$H = I - 2vv^T$ when $\|v\|=1$ { since $\| \begin{pmatrix} 1 \\ -\sqrt{3} \end{pmatrix} \| = 2 \Rightarrow H \begin{pmatrix} 1 \\ -\sqrt{3} \end{pmatrix} = \begin{pmatrix} 2 \\ 0 \end{pmatrix}$ }

take $\hat{v} = \frac{u}{\|u\|}$, $u = \begin{pmatrix} 1 \\ -\sqrt{3} \end{pmatrix}$, $\|u\| = 2$
 $\hat{v} = \begin{pmatrix} 1 \\ -\sqrt{3} \end{pmatrix} - 2 \begin{pmatrix} 1 \\ 0 \end{pmatrix} = \begin{pmatrix} -1 \\ -\sqrt{3} \end{pmatrix}$ $\|\hat{v}\| = \sqrt{1+3} = 2$

$v = \frac{\hat{v}}{\|\hat{v}\|} = \frac{1}{2} \begin{pmatrix} -1 \\ -\sqrt{3} \end{pmatrix}$ v defines $H: H = I - 2vv^T$

1.2

$$\left\{ \begin{array}{l} H = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} - 2 \cdot \frac{1}{2} \begin{pmatrix} -1 \\ -\sqrt{3} \end{pmatrix} \cdot \frac{1}{2} \begin{pmatrix} -1 & -\sqrt{3} \end{pmatrix} \\ H = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} - \frac{1}{2} \begin{pmatrix} 1 & \sqrt{3} \\ \sqrt{3} & 3 \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & -\frac{1}{2}\sqrt{3} \\ -\frac{1}{2}\sqrt{3} & -\frac{1}{2} \end{pmatrix} \\ \text{check } H \begin{pmatrix} 1 \\ -\sqrt{3} \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & -\frac{1}{2}\sqrt{3} \\ -\frac{1}{2}\sqrt{3} & -\frac{1}{2} \end{pmatrix} \begin{pmatrix} 1 \\ -\sqrt{3} \end{pmatrix} = \begin{pmatrix} 2 \\ 0 \end{pmatrix} \quad \checkmark \end{array} \right.$$

advantages of using v instead of H

0.8

- v is vector, H is matrix $\Rightarrow v$ needs less storage memory
- computing $x - 2vv^T x$ is cheaper in computational effort than first computing H and then Hx

d) bring following matrix in Hessenberg form using a similarity transformation

$$A = \begin{bmatrix} -1 & 1 & \sqrt{5} \\ -1 & -2 & 6 \\ \sqrt{3} & -4 & -7 \end{bmatrix}$$

create a "zero" in position $A_{3,1}$

note $A(2:3,1) = \begin{pmatrix} -1 \\ +\sqrt{3} \end{pmatrix}$, with the H of part (c) this vector can be transformed to $\begin{pmatrix} -2 \\ 0 \end{pmatrix}$

0.9 \Rightarrow take transformation matrix $T = \begin{bmatrix} 1 & 0 \\ 0 & H \end{bmatrix}$

note $T^{-1} = \begin{bmatrix} 1 & 0 \\ 0 & H^{-1} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & H \end{bmatrix}$ $H^T H = I$
 $H^{-1} = H$

\Rightarrow apply similarity transformation on A

$$T^{-1} A T = \begin{bmatrix} 1 & 0 \\ 0 & H \end{bmatrix} \begin{bmatrix} -1 & 1 & \sqrt{5} \\ -1 & -2 & 6 \\ \sqrt{3} & -4 & -7 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & H \end{bmatrix}$$

$$\Rightarrow T^{-1} A T = \begin{bmatrix} -1 & 1 & \sqrt{5} \\ H\left(\frac{-1}{\sqrt{3}}\right) & H(-2) & H\left(\frac{6}{-7}\right) \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & H \end{bmatrix}$$

$$= \begin{bmatrix} -1 & 1 & \sqrt{5} \\ -2 & H(-2) & H\left(\frac{6}{-7}\right) \\ 0 & H(-4) & H\left(\frac{6}{-7}\right) \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & H \end{bmatrix}$$

$$= \begin{bmatrix} -1 & 1 & \sqrt{5} \\ -2 & \left(H\left(\frac{-2}{-4}\right) \cdot H\left(\frac{6}{-7}\right) \right) \\ 0 & \left(H\left(\frac{-2}{-4}\right) \cdot H\left(\frac{6}{-7}\right) \right) \end{bmatrix} H = \begin{bmatrix} -1 & * & * \\ -2 & * & * \\ 0 & * & * \end{bmatrix}$$

Hessenberg form

e. first transforming A to Hessenberg form, i.e. $T^{-1} A T$ is advantageous when applying QR method

1. Similarity transformation preserves the eigenvalues

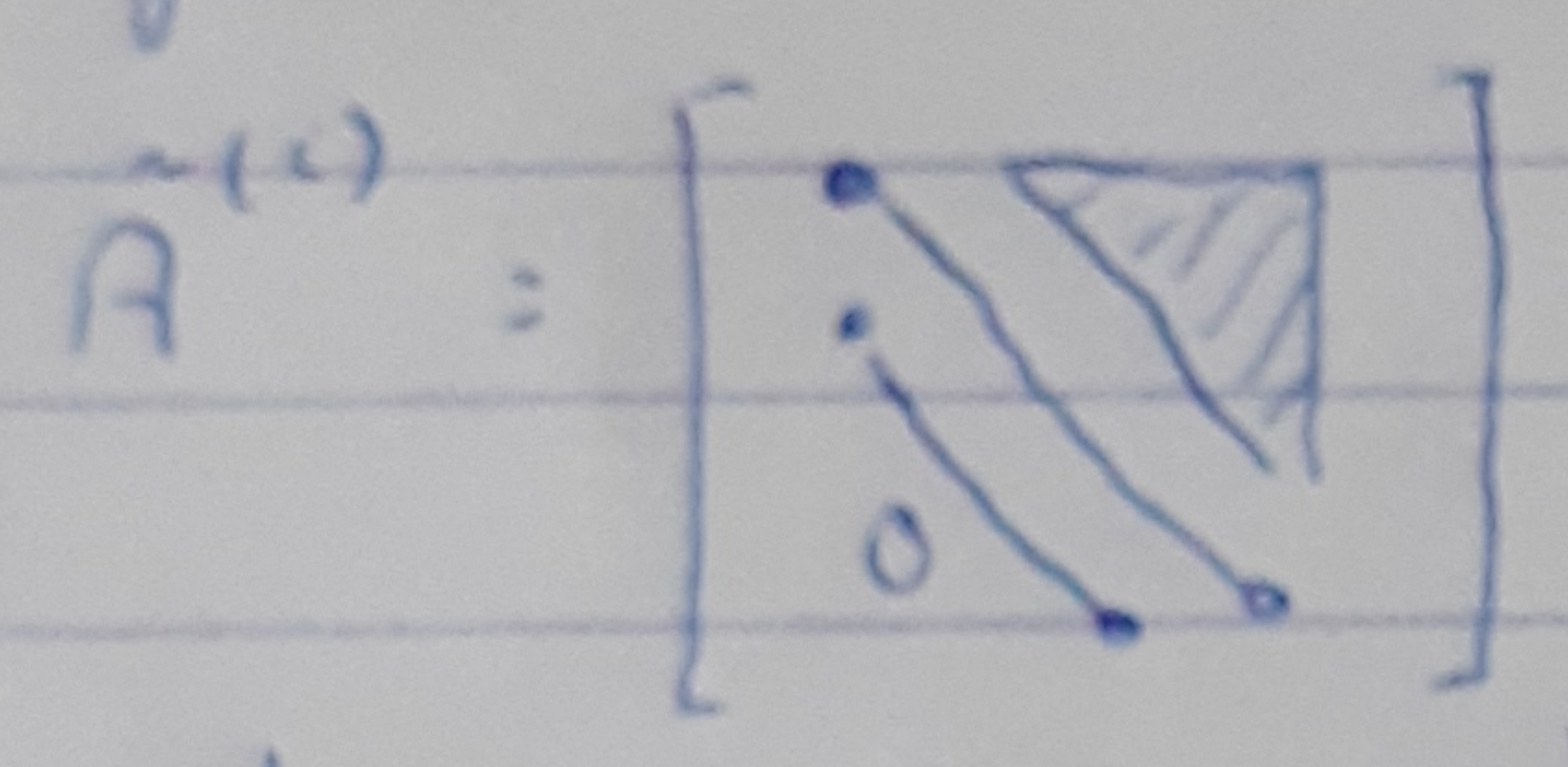
0.2

2. when starting with a matrix \tilde{A} which is Hessenberg, the iteration $\tilde{A}^{(i+1)}$ in the QR method are Hessenberg as well

3. QR method is essentially
$$\left. \begin{aligned} Q^{(i)} R^{(i)} &= \tilde{A}^{(i)} \\ \tilde{A}^{(i+1)} &= R^{(i)} Q^{(i)} \end{aligned} \right\} i=0,1,2,\dots$$

making the QR factorization becomes simpler and computing RQ is simpler

Making QR :



0.6

- only a 2×2 Householder matrix is needed to obtain a zero at position $(2,1)$ and only the first two rows need to be multiplied by the Householder matrix this is relatively cheap
- repeat for row 3 to make position $(3,2)$ zero
for row 4 to make position $(4,3)$ zero
etc.

Similar for computing RQ