

Q1

$$a-b-c-d-e-f-g-h-i-j-k$$

$$2 \ 0 \ 2 \ 2 \ 0 \ 8 \ 0 \ 8 \ 0 \ 6 \ 9$$

20220808069

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$$X_i: \begin{array}{|c|c|c|c|c|c|} \hline 1 & 1.5 & 1.9 & 2.3 & 2.6 & 3 \\ \hline \end{array}$$

$$y_i: \begin{array}{|c|c|c|c|c|c|} \hline 2 & 2 & 7 & 10 & 35 & 56 \\ \hline \end{array}$$

a) Find the least squares regression line for the given data using QR factorization of the design matrix

$$y = ax + b \Rightarrow \begin{array}{l} a + b = 2 \\ 1.5a + b = 2 \\ 1.9a + b = 7 \end{array} \quad \begin{array}{l} 2.3a + b = 10 \\ 2.6a + b = 35 \\ 3a + b = 56 \end{array}$$

$$Ax = b$$

$$A = \begin{bmatrix} 1 & 1 & 2 \\ 1.5 & 1 & 2 \\ 1.9 & 1 & 7 \\ 2.3 & 1 & 10 \\ 2.6 & 1 & 35 \\ 3 & 1 & 56 \end{bmatrix}$$

$$a_1 = \begin{bmatrix} 1 \\ 1.5 \\ 1.9 \\ 2.3 \\ 2.6 \\ 3 \end{bmatrix}$$

$$a_2 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

$$a_1, a_2 = 1 + 1.5 + 1.9 + 2.3 + 2.6 + 3$$

$$= 12.3 \neq 0$$

They are not orthogonal

so, we need to make them orthogonal, let's use Gram-Schmidt method.

$$u_1 = a_1$$

$$u_2 = a_2 - \frac{a_2 \cdot u_1}{u_1 \cdot u_1} u_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} - \frac{12.3}{27.91} \begin{bmatrix} 1 \\ 1.5 \\ 1.9 \\ 2.3 \\ 2.6 \\ 3 \end{bmatrix} = \begin{bmatrix} 1 - 0.4407 \\ 1 - 0.66105 \\ 1 - 0.83733 \\ 1 - 1.01361 \\ 1 - 1.14582 \\ 1 - 1.3221 \end{bmatrix}$$

$$u_1 \cdot u_1 = 1 + (1.5)^2 + (1.9)^2 + (2.3)^2 + (2.6)^2 + 3^2 = 27.91$$

$$\|u_1\| = 5.2829$$

$$u_2 \cdot u_2 = (0.5593)^2 + (0.33895)^2$$

$$+ (0.16267)^2 + (0.1361)^2$$

$$+ (0.14582)^2 + (0.3221)^2$$

$$\approx 0.5977$$

$$u_2 = \begin{bmatrix} 0.5593 \\ 0.33895 \\ 0.16267 \\ -0.1361 \\ -0.14582 \\ -0.3221 \end{bmatrix}$$

$$e_1 = \frac{u_1}{\|u_1\|} = \begin{bmatrix} 0.18928 \\ 0.28392 \\ 0.35963 \\ 0.48534 \\ 0.49213 \\ 0.56784 \end{bmatrix}$$

$$e_2 = \frac{u_2}{\|u_2\|} = \begin{bmatrix} 0.73482 \\ 0.44531 \\ 0.21372 \\ -0.01778 \\ -0.19157 \\ -0.42315 \end{bmatrix}$$

$$Q = \begin{bmatrix} 0.18928 & 0.73482 \\ 0.28392 & 0.44531 \\ 0.35963 & 0.21372 \\ 0.48534 & -0.01778 \\ 0.49213 & -0.19157 \\ 0.56784 & -0.42315 \end{bmatrix}$$

$$A = 6 \times 2 \quad R = 2 \times 2 \quad R = \begin{bmatrix} r_{11} & r_{12} \\ 0 & r_{22} \end{bmatrix} \quad r_{11} = a_1 \cdot e_1 \quad r_{12} = a_2 \cdot e_1 \\ r_{22} = a_2 \cdot e_2$$

$$r_{11} = a_1 \cdot e_1 = 1 \cdot 0,18928 + 1,5 \cdot 0,28392 + 1,9 \cdot 0,35963 + 2,3 \cdot 0,43534 \\ + 2,6 \cdot 0,49213 + 3 \cdot 0,56784 \\ = 5,282797$$

$$r_{12} = a_2 \cdot e_1 = 1 \cdot 0,18928 + 0,28392 + 0,35963 + 0,43534 + 0,49213 + 0,56784 \\ = 2,32814$$

$$r_{22} = a_2 \cdot e_2 = 0,73482 + 0,44631 + 0,21372 - 0,01788 - 0,19157 - 0,42315 \\ = 0,76116$$

$$R = \begin{bmatrix} 5,282797 & 2,32814 \\ 0 & 0,76116 \end{bmatrix}, \quad R^{-1} = \frac{1}{\det(R)} \begin{bmatrix} 0,76116 & -2,32814 \\ 0 & 5,282797 \end{bmatrix}$$

\downarrow
 $4,02105$

$$X = R^{-1} \underbrace{Q^T b}_{\text{first second}} = \begin{bmatrix} 0,18929 & -0,57898 \\ 0 & 1,31378 \end{bmatrix}$$

$$\begin{pmatrix} a \\ b \end{pmatrix} = \begin{bmatrix} 0,18929 & -0,57898 \\ 0 & 1,31378 \end{bmatrix} \cdot \begin{bmatrix} 56,8408 \\ -26,72385 \end{bmatrix}$$

$$\begin{pmatrix} a \\ b \end{pmatrix} = \begin{pmatrix} 26,23196 \\ -35,10925 \end{pmatrix}, \quad y \approx 26,23196x - 35,10925$$

Solution section added with both numpy library and
Saby library. There is a little difference between the results.

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Question1a.java Code and Output

```
Question1a.py
Question1a.py > ...
1 import numpy as np
2 import scipy.linalg
3
4 # Öğrenci ID: 20220808069 -> a=2, c=2, j=6, k=9
5 a_id = 2
6 c_id = 2
7 j_id = 6
8 k_id = 9
9
10 x_i = np.array([1, 1.5, 1.9, 2.3, 2.6, 3])
11 y_i_formulas = [
12     c_id,
13     a_id,
14     j_id + 1,
15     k_id + 1,
16     (k_id + 1) * (j_id + 1) / 2,
17     k_id * j_id + 2
18 ]
19 y_i = np.array(y_i_formulas)
20
21 print("Data Points:")
22 for i in range(len(x_i)):
23     print(f"x_{i+1} = {x_i[i]}, y_{i+1} = {y_i[i]}")
24 print("-" * 30)
25
26 A = np.vstack([x_i, np.ones(len(x_i))]).T
27
28 print("Design Matrix A:")
29 print(A)
30 print("-" * 30)
31
32 print("y Vektörü:")
33 print(y_i)
34 print("-" * 30)
35
36 # Solution 1: using numpy.linalg.qr
37 print("QR Decomposition with NumPy:")
38 Q_np, R_np = np.linalg.qr(A)
39
40 print("Q (NumPy):")
41 print(Q_np)
42 print("\nR (NumPy):")
43 print(R_np)
44 print("-" * 30)
```

```
Question1a.py
Question1a.py > ...
45
46 # Q.T * y
47 qty_np = Q_np.T @ y_i
48 print("Q.T @ y (NumPy):")
49 print(qty_np)
50 print("-" * 30)
51
52 # R * beta = qty_np
53 # beta = [beta1, beta0]
54 beta_np = np.linalg.solve(R_np, qty_np)
55 beta1_np = beta_np[0]
56 beta0_np = beta_np[1]
57
58 print(f"Coefficients (beta) found with NumPy: {beta_np}")
59 print(f"Regression Line (NumPy): y = {beta1_np:.4f}x + {beta0_np:.4f}")
60 print(f"Our Manuel Solution with Calculator :    y = 26.2338x - 35.1097")
61 print("-" * 50)
62
63 # Solution 2: using scipy.linalg.qr
64 print("QR Decomposition with SciPy:")
65 Q_sp, R_sp = scipy.linalg.qr(A, mode='economic')
66
67 print("Q (SciPy):")
68 print(Q_sp)
69 print("\nR (SciPy):")
70 print(R_sp)
71 print("-" * 30)
72
73 # R * beta = Q.T * y to be solved
74 qty_sp = Q_sp.T @ y_i
75 print("Q.T @ y (SciPy):")
76 print(qty_sp)
77 print("-" * 30)
78
79 beta_sp = scipy.linalg.solve_triangular(R_sp, qty_sp, lower=False)
80 beta1_sp = beta_sp[0]
81 beta0_sp = beta_sp[1]
82
83 print(f"Coefficients found with SciPy (beta): {beta_sp}")
84 print(f"Regression Line (SciPy): y = {beta1_sp:.4f}x + {beta0_sp:.4f}")
85 print("-" * 50)
86
87 #Check directly with numpy.linalg.lstsq
88 print("Direct Solution (Control) with NumPy lstsq:")
89 beta_lstsq, residuals, rank, s_values = np.linalg.lstsq(A, y_i, rcond=None)
90 beta1_lstsq = beta_lstsq[0]
91 beta0_lstsq = beta_lstsq[1]
```

```
Question1a.py X
Question1a.py > ...
86
87 #Check directly with numpy.linalg.lstsq
88 print("Direct Solution (Control) with NumPy lstsq:")
89 beta_lstsq, residuals, rank, s_values = np.linalg.lstsq(A, y_i, rcond=None)
90 beta1_lstsq = beta_lstsq[0]
91 beta0_lstsq = beta_lstsq[1]
92
93 print(f"Coefficients found with lstsq (beta): {beta_lstsq}")
94 print(f"Regression Line (lstsq): y = {beta1_lstsq:.4f}x + {beta0_lstsq:.4f}")
95 print("-" * 50)
96
97 -----
98
99 Data Points:
100 x_1 = 1.0, y_1 = 2.0
101 x_2 = 1.5, y_2 = 2.0
102 x_3 = 1.9, y_3 = 7.0
103 x_4 = 2.3, y_4 = 10.0
104 x_5 = 2.6, y_5 = 35.0
105 x_6 = 3.0, y_6 = 56.0
106
107 -----
108
109 Design Matrix A:
110 [[1. 1. ]
111  [1.5 1. ]
112  [1.9 1. ]
113  [2.3 1. ]
114  [2.6 1. ]
115  [3. 1. ]]
116
117 -----
118
119 y Vektörü:
120 [ 2.  7. 10. 35. 56.]
121
122 -----
123
124 QR Decomposition with NumPy:
125 Q (NumPy):
126 [[-0.18928669 -0.73479802]
127  [-0.28393004 -0.4453036 ]
128  [-0.35964472 -0.21370807]
129  [-0.43535939 -0.01788746]
130  [-0.4921454  0.19158411]
131  [-0.56786008  0.42317964]]
132
133 R (NumPy):
134 [[-5.28299158 -2.32822631]
135  [ 0.         -0.76115848]]
136
137 -----
138
139 Q.T @ y (NumPy):
140 [-56.84279364  26.72621841]
```

```
-----
Q.T @ y (NumPy):
[-56.84279364  26.72621841]
-----
Coefficients (beta) found with NumPy: [ 26.23376623 -35.11255411]
Regression Line (NumPy): y = 26.2338x - 35.1126
Our Manuel Solution with Calculator :    y = 26.23196x - 35.10925
-----
```

```
-----
QR Decomposition with SciPy:
Q (SciPy):
[[-0.18928669 -0.73479802]
 [-0.28393004 -0.4453036 ]
 [-0.35964472 -0.21370807]
 [-0.43535939 -0.01788746]
 [-0.4921454  0.19158411]
 [-0.56786008  0.42317964]]
```

```
R (SciPy):
[[-5.28299158 -2.32822631]
 [ 0.         -0.76115848]]
-----
```

```
-----
Q.T @ y (SciPy):
[-56.84279364  26.72621841]
-----
Coefficients found with SciPy (beta): [ 26.23376623 -35.11255411]
Regression Line (SciPy): y = 26.2338x + -35.1126
-----
```

```
-----
Direct Solution (Control) with NumPy lstsq:
Coefficients found with lstsq (beta): [ 26.23376623 -35.11255411]
Regression Line (lstsq): y = 26.2338x + -35.1126
-----
```

We will add java codes as a zip file.

b) Use gradient method to compute same least squares regression line

Initial point: $x_0 = (0,0)$ or $x_0(1,1)$ or any randomly generated point.

Learning rate: $\alpha = 0.001$

$$\epsilon = 0.005$$

Stopping criterion $\|\nabla f\| < \epsilon$

x_i	1	1.5	1.9	2.3	2.6	3
y_i	2	2	7	10	35	56

$$y = ax + b$$

we will use gradient descent method

$f(b,a) = \sum_{i=1}^6 (y_i - b - a \cdot x_i)^2$, to solve this problem, firstly we need to do initialization

lets choose $x_0 = (0,0)$

$$\alpha = 0.001 \quad \epsilon = 0.005$$

$$\text{Then, } x_1 = x_0 - \alpha \cdot \nabla f(x_0)$$

$$x_2 = x_1 - \alpha \cdot \nabla f(x_1)$$

\vdots

$$x_n = x_{n-1} - \alpha \cdot \nabla f(x_{n-1})$$

When $\|\nabla f(x)\| < \epsilon$ we stop, and x_n is the approximate value for global minimum.


It is hard to solve manually. So, we write a python code to solve (we added the code block and output at the end).

According to result of code, $a = 26.2317$

$$b = -35.1078$$

$$y = 26.2317x - 35.1078$$

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Question1b.java Code and Output

```
Question1b.py > ...
1 import numpy as np
2
3 # x_i = [1, 1.5, 1.9, 2.3, 2.6, 3]
4 # y_i = [2, 2, 7, 10, 35, 56]
5 data_x = np.array([1, 1.5, 1.9, 2.3, 2.6, 3])
6 data_y = np.array([2., 2., 7., 10., 35., 56.])
7
8 alpha = 0.001
9 epsilon = 0.005
10 max_iterations = 500000
11
12 beta = np.array([0.0, 0.0]) # beta[0] = beta_0 (intercept), beta[1] = beta_1 (slope)
13
14 print(f"Başlangıç Katsayıları (beta0, beta1): {beta}")
15 print(f"Öğrenme Oranı (alpha): {alpha}")
16 print(f"Durdurma Toleransı (epsilon): {epsilon}")
17 print("-" * 50)
18
19 # To store the iteration history
20 cost_history = []
21 grad_norm_history = []
22
23 # Gradient Descent Cycle
24 for iteration in range(max_iterations):
25     beta0_current = beta[0]
26     beta1_current = beta[1]
27
28     # Predicted y values: y_pred = beta0 * x + beta1
29     y_pred = beta0_current * data_x + beta1_current
30
31     # Hata terimleri: hata = y_pred - y_actual
32     errors = y_pred - data_y
33
34     # Cost Function (Sum of Squared Errors) - For follow-up
35     cost = np.sum(errors**2)
36     cost_history.append(cost)
37
38     # Calculation of Gradients
39     # df/dbeta0 = 2 * sum(errors)
40     # df/dbeta1 = 2 * sum(errors * data_x)
41     grad_beta0 = 2 * np.sum(errors)
42     grad_beta1 = 2 * np.sum(errors * data_x)
43     gradient = np.array([grad_beta0, grad_beta1])
44
45     # Norm of the gradient - for the stopping criterion
46     grad_norm = np.linalg.norm(gradient)
```

```
Question1b.py > ...
45 # Norm of the gradient - for the stopping criterion
46 grad_norm = np.linalg.norm(gradient)
47 grad_norm_history.append(grad_norm)
48
49 # Stop Criteria
50 if grad_norm < epsilon:
51     print(f"*** Stop criterion met! ((iteration+1). iteration) ***")
52     break
53
54 # Updating Coefficients
55 beta = beta - alpha * gradient
56
57 # Print progress status occasionally (optional)
58 if (iteration + 1) % 50000 == 0 or iteration < 5:
59     print(f"Iter {iteration+1:6}: beta0={beta[0]:.4f}, beta1={beta[1]:.4f}, ||Vf||={grad_norm:.4f}")
60
61
62 if iteration == max_iterations - 1 and grad_norm >= epsilon:
63     print(f"Uyarı: Maximum number of iterations ({max_iterations}) ulaşıldı.")
64     print(f"The gradient norm ({grad_norm:.6f}) is still greater than or equal to")
65
66 print("-" * 50)
67 print("Gradient Descent Method Result:")
68 print(f"Iteration Number : {iteration + 1}")
69 print(f"beta0 (intercept) : {beta[0]:.4f}")
70 print(f"beta1 (slope) : {beta[1]:.4f}")
71 print(f"Final Gradient Norm : {grad_norm:.6f} (Hedef < {epsilon})")
72 print(f"The Last Mistake (Cost) : {cost:.2f}")
73 print(f"Regression Line : y = {beta[1]:.4f}x + {beta[0]:.4f}")
74 print("-" * 50)
75
76 # The result of (a) for comparison
77 beta1_qr = 26.23378378
78 beta0_qr = -35.10972973
79 print("Comparison (Problem 1a - QR/lstsq):")
80 print(f"beta0 (intercept) : {beta0_qr:.4f}")
81 print(f"beta1 (slope) : {beta1_qr:.4f}")
82 print(f"Regresyon Line : y = {beta1_qr:.4f}x + {beta0_qr:.4f}")
83 print("-" * 50)
84
```

```
Question1b.py X
Question1b.py > ...
1 import numpy as np
2
3 # x_i = [1, 1.5, 1.9, 2.3, 2.6, 3]
4 # y_i = [2, 2, 7, 10, 35, 56]
5 data_x = np.array([1, 1.5, 1.9, 2.3, 2.6, 3])
6 data_y = np.array([2., 2., 7., 10., 35., 56.])
7
8 alpha = 0.001
9 epsilon = 0.005
10 max_iterations = 500000
11
12 beta = np.array([0.0, 0.0]) # beta[0] = beta_0 (intercept), beta[1] = beta_1 (slope)

PROBLEMS OUTPUT DEBUG CONSOLE TERMINAL PORTS

PS C:\Users\burak\OneDrive\Masaüstü\lineer\Assignment2>
& C:/Users/burak/AppData/Local/Programs/Python/Python312/python.exe c:/Users/burak/OneDrive/Masaüstü/lineer/Assignment2/Question1b.py
Başlangıç Katsayıları (beta0, beta1): [0. 0.]
Öğrenme Oranı (alpha): 0.001
Durdurma Toleransı (epsilon): 0.005

-----
Iter   1: beta0=0.2240, beta1=0.6006, ||Vf||=641.011981, Cost=4518.00
Iter   2: beta0=0.4305, beta1=1.1622, ||Vf||=598.340939, Cost=4120.78
Iter   3: beta0=0.6208, beta1=1.6873, ||Vf||=558.535174, Cost=3774.68
Iter   4: beta0=0.7958, beta1=2.1784, ||Vf||=521.404001, Cost=3473.09
Iter   5: beta0=0.9567, beta1=2.6379, ||Vf||=486.769534, Cost=3210.26

*** Stop criterion met! (9321. iteration) ***

Gradient Descent Method Result:
Iteration Number : 9321
beta0 (intercept) : -35.1078
beta1 (slope) : 26.2317
Final Gradient Norm : 0.004998 (Hedef < 0.005)
The Last Mistake (Cost) : 572.61
Regression Line : y = 26.2317x + -35.1078

-----
Comparison (Problem 1a - QR/lstsq):
beta0 (intercept) : -35.1097
beta1 (slope) : 26.2338
Regresyon Line : y = 26.2338x + -35.1097

-----
PS C:\Users\burak\OneDrive\Masaüstü\lineer\Assignment2>
```

Q2 / 20220808069

$$J=6, k=9$$

Consider the following 4×4 linear system.

$$17x_1 - x_2 + 2x_3 + x_4 = 8$$

$$x_1 + 20x_2 - 3x_3 - x_4 = 10$$

$$2x_1 - x_2 + 13x_3 - 2x_4 = 10$$

$$x_1 + 2x_2 + 4x_3 + 10x_4 = 18$$

In this problem, your goal is to approximately solve this system using Jacobi or Gauss-Seidel iteration.

Initial guess : $x_0 = (0, 0, 0)^T$

Stopping criterion : $xTOL = \|x_n - x_{n+1}\| < \epsilon$
where $\|\cdot\|$ is the maximum norm.

$$\epsilon = 0.01$$

$$Ax = b$$

$$A = \begin{bmatrix} 17 & -1 & 2 & 1 \\ 1 & 20 & -3 & -1 \\ 2 & -1 & 13 & -2 \\ 1 & 2 & 4 & 10 \end{bmatrix} \begin{bmatrix} 8 \\ 10 \\ 10 \\ 18 \end{bmatrix}$$

Since the absolute largest values in each column are on the diagonal, we can start to leave those values alone

$$17x_1 = 8 + x_2 - 2x_3 - x_4 \Rightarrow x_1^{(k+1)} = \frac{1}{17} (8 + x_2^{(k)} - 2x_3^{(k)} - x_4^{(k)})$$

$$x_2^{(k+1)} = \frac{1}{20} (10 - x_1^{(k)} + 3x_3^{(k)} + x_4^{(k)})$$

$$x_3^{(k+1)} = \frac{1}{13} (-2x_1^{(k)} + x_2^{(k)} + 2x_4^{(k)})$$

$$x_4^{(k+1)} = \frac{1}{10} (18 - x_1^{(k)} - 2x_2^{(k)} - 4x_3^{(k)})$$

$$x_1^{(0)}, x_2^{(0)}, x_3^{(0)}, x_4^{(0)} = 0$$

Iteration 1: ($k=0, x_n^{(0)}$)

$$x_1^{(1)} = \frac{1}{17} (8 + 0 - 2 \cdot 0 - 0) = \frac{8}{17} \approx 0.470588$$

$$x_2^{(1)} = \frac{1}{20} (10 - 0 + 3 \cdot 0 + 0) = \frac{10}{20} = 0.5$$

$$x_3^{(1)} = \frac{1}{13} (0) = \frac{0}{13} = 0$$

$$x_4^{(1)} = \frac{1}{10} (18) = \frac{18}{10} = 1.8$$

$$XTOL_1 = \max \{ |0.470588 - 0|, |0.5 - 0|, |0 - 0|, |1.8 - 0| \}$$

$$XTOL_1 = 1.8$$

$$1.8 \gg 0.01$$

continue..

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Iteration 2

$$x_1^{(2)} = \frac{1}{17} (8 + 0.5 - 2.0 - 1.8) = \frac{1}{17} \cdot 6.7 \approx 0.394118$$

$$x_2^{(2)} = \frac{1}{20} (10 - 0.470588 + 3.0 + 1.8) = \frac{1}{20} \cdot 11.329412 \approx 0.566471$$

$$x_3^{(2)} = \frac{1}{13} \cdot 1$$

$$x_4^{(2)} = \frac{1}{10} (18 - 0.470588 - 2.0 \cdot 0.5 - 4.0) \approx 1.652941$$

$$XTOL_2 = \max \{ |0.394118 - 0.470588|, |0.566471 - 0.5|, |0.242986 - 0|, |1.652941 - 1.8| \}$$

$$XTOL_2 = 0.242986 \geq 0.01 \text{ Continue.}$$

Iteration 3

$$x_1^{(3)} = \frac{1}{17} (8 + 0.566471 - 2.0 \cdot 0.242986 - 1.652941) = \frac{1}{17} \cdot 6.427558 \approx 0.378092$$

$$x_2^{(3)} = \frac{1}{20} (10 - 0.394118 + 3 \cdot 0.242986 + 1.652941) = \frac{1}{20} \cdot (10 - 0.394118 + 0.728958 + 1.652941) = \frac{1}{20} \cdot (11.987781) \approx 0.599389$$

$$x_3^{(3)} = \frac{1}{13} (-2 \cdot 0.394118 + 0.566471 + 2 \cdot 1.652941) = \frac{1}{13} (3.084117) \approx 0.237240$$

$$x_4^{(3)} = \frac{1}{10} (18 - 0.394118 - 2 \cdot 0.566471 - 4 \cdot 0.242986) = \frac{1}{10} (15.501996) \approx 1.5501$$

$$XTOL_3 = 0.102481 \geq 0.01 \text{ Continue}$$

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Iteration 4

$$X_1^{(4)} = \frac{1}{17} (18 + 0.599389 - 2 \cdot 0.237240 - 1.550100) = \frac{1}{17} \cdot 6.574809 \approx 0.386753$$

$$X_2^{(4)} = \frac{1}{20} (10 - 0.378092 + 3 \cdot 0.237240 + 1.5501)$$

$$= \frac{1}{20} (11.883728) \approx 0.594186$$

$$X_3^{(4)} = \frac{1}{13} (-2 \cdot 0.378092 + 0.599389 + 2 \cdot 1.5501) = \frac{1}{13} \cdot (2.943405) \approx 0.226416$$

$$X_4^{(4)} = \frac{1}{10} (18 - 0.378092 - 2 \cdot 0.599389 - 4 \cdot 0.237240) = \frac{1}{10} (15.47417) \approx 1.547417$$

$$XTOL_4 = \max \{ |0.386753 - 0.378092|, |0.594186 - 0.599389|, |0.226416 - 0.237240|, |1.547417 - 1.5501| \}$$
$$XTOL_4 = 0.010824 \geq 0.01 \text{ Continue. (I think, we're close!)}$$

Iteration 5

$$X_1^{(5)} = \frac{1}{17} (18 + 0.594186 - 2 \cdot 0.226416 - 1.547417) = \frac{1}{17} (6.593937) \approx 0.387879$$

$$X_2^{(5)} = \frac{1}{20} (10 - 0.386753 + 3 \cdot 0.226416 + 1.547417) = \frac{1}{20} \cdot 11.839912 \approx 0.591996$$

$$X_3^{(5)} = \frac{1}{13} (-2 \cdot 0.386753 + 0.594186 + 2 \cdot 1.547417) = \frac{1}{13} (2.915514) \approx 0.224270$$

$$X_4^{(5)} = \frac{1}{10} (18 - 0.386753 - 2 \cdot 0.594186 - 4 \cdot 0.226416) = \frac{1}{10} \cdot 15.519211 \approx 1.551921$$

$$XTOL_5 = \max \{ |0.387879 - 0.386753|, |0.591996 - 0.594186|, |0.224270 - 0.226416|, |1.551921 - 1.547417| \}$$

$$XTOL_5 = 0.004504 < 0.01 \text{ Stop.}$$

$$X_n = X^5: (0.387879, 0.591996, 0.224270, 1.551921)$$

$$XTOL \approx 0.004504$$

we use 6 digit

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Question2.java Code and Output

```
Question2 X
1 import numpy as np
2
3 j = 5
4 k_id = 9 # k can be a keyword in Python, so I used k_id
5
6 A = np.array([
7     [11 + j, -1, 2, 1],
8     [1, 11 + k_id, -1, -1],
9     [2, -1, 19 - j, -2],
10    [1, 2, 4, 19 - k_id]
11 ], dtype=float)
12
13 b = np.array([0, 10, 0, 10], dtype=float)
14
15 print("A Matrisi:\n", A)
16 print("\nb Vektörü:\n", b)
17
18 # cInitial parameters
19 x_old = np.array([0.0, 0.0, 0.0, 0.0]) # x^(0)
20 epsilon = 0.01
21 max_iterations = 100
22 n = len(b)
23
24 print(f"Initial x^(0): {x_old}")
25 print(f"Epsilon: {epsilon}")
26 print("-" * 30)
27 print("-" * 30)
28
29 for iteration in range(max_iterations):
30     x_new = np.zeros_like(x_old)
31
32     # Apply Jacobi iteration formulae
33     # x_new[0] (x1)
34     x_new[0] = (b[0] - A[0,1]*x_old[1] - A[0,2]*x_old[2] - A[0,3]*x_old[3]) / A[0,0]
35     # x_new[1] (x2)
36     x_new[1] = (b[1] - A[1,0]*x_old[0] - A[1,2]*x_old[2] - A[1,3]*x_old[3]) / A[1,1]
37     # x_new[2] (x3)
38     x_new[2] = (b[2] - A[2,0]*x_old[0] - A[2,1]*x_old[1] - A[2,3]*x_old[3]) / A[2,2]
39     # x_new[3] (x4)
40     x_new[3] = (b[3] - A[3,0]*x_old[0] - A[3,1]*x_old[1] - A[3,2]*x_old[2]) / A[3,3]
41
42     # Durumda kriteri: xTOL = ||x_new - x_old||_1
43     xTOL = np.max(np.abs(x_new - x_old))
44     print(f"Iteration {iteration + 1}:")
45     print(f"    x_new = {np.round(x_new, 6)}")
46     print(f"    xTOL = {xTOL:.6f}")
47
48     if xTOL < epsilon:
49         print("-" * 30)
50         print(f"Convergence {iteration + 1}. provided in iteration.")
51         x_final = x_new
52         xTOL_final = xTOL
53         break
54
55     x_old = x_new.copy() # Bir sonraki iterasyon için x_old'u güncelle
56     print("-" * 30)
57
58     if iteration == max_iterations - 1:
59         print("-" * 30)
60         print("Maximum number of iterations reached, no convergence achieved.")
61         x_final = x_new
62         xTOL_final = xTOL
63
64 print("\nConclusion:")
65 print(f"Final approximate solution x_n: {np.round(x_final, 6)}")
66 print(f"The xTOL value that caused the stop: {xTOL_final:.6f}")
67 # Kontrol için (opsiyonel): Ax - b ne kadar yakın sıfıra?
68 residual = np.dot(A, x_final) - b
69 print(f"xTOL = {xTOL:.6f} (Ax - b): {np.round(residual, 6)}")
```

```
-----
Iteration 5:
  x_new = [0.387879 0.591996 0.22427  1.551921]
  xTOL   = 0.004504
-----
  x_new = [0.387879 0.591996 0.22427  1.551921]
  xTOL   = 0.004504
-----
Convergence5. provided in iteration.

  xTOL   = 0.004504
-----
```