Phase 1 Report

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1. Pseudo-Code:

For solving system of linear equations with alphabetical coefficients Function alphabeticalSolution(matrix):

If number of rows of matrix != number of unique rows: return "No Solution For Matrix"

Define symbolic variables for each of the unknowns based on the number of rows

variables = generate symbolic variables ('x', 'y', ...,)

Convert string coefficients to symbolic variables symbolic_matrix = Empty list

For each row i in matrix:

symbolic_row = Empty list

For each element j in row i:

If element is a string: Convert to symbolic variable and add to symbolic row

Else: Add the numeric value to symbolic_row

Add symbolic_row to symbolic_matrix

Define the system of equations equations = Empty list

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For each row i in symbolic matrix:
               equation = 0
               For each element j in row i (except the last one):
                     equation = equation + (element at i,j * corresponding variable in
              variables)
              Add (equation, last element in row i) to equations
       # Solve the system of equations
       solutions = Solve equations for variables using "sympy.solve()"
       return solutions
# Helper functions for different methods
Function forward Elimination(augmented matrix,n):
    for i=0 to n-1:
       # Find the row with the maximum absolute value in column i
       max row = row with maximum value in column i
Swap rows i and max_row
       # Check if the pivot element is zero or very close to zero
      if pivot element is too small (close to zero):
         return "Pivot element is zero or very small, cannot proceed."
       # Perform the row reduction
       for j = i + 1to n-1:
         factor = augmented_matrix[j, i] / augmented_matrix[i, i]
         augmented_matrix[j, i:] -= factor * augmented_matrix[i, i:]
    return augmented_matrix
Function forward_substitution(augmented_matrix, n):
x = array of zeroes with length n
for i=0 to n-1:
              if augmented_matrix[i, i] == 0:
                     return "System has no unique solution."
              x[i] = augmented_matrix[i, -1] / augmented_matrix[i, i]
              for j=i + 1 to n-1:
                      augmented_matrix[j, -1] -= augmented_matrix[j, i] * x[i]
return x, augmented_matrix
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Function backward Elimination(augmented matrix,n):
   for i = n-1 to 0:
       Normalize the pivot row (make the pivot element equal to 1
       # Eliminate the elements above the pivot
       for j=i-1 to 0: # Go through rows above the pivot
             factor = augmented_matrix[j, i]
             each element in row j from i to n-1 -= factor * each element in row i from
i to n-1
   return augmented matrix
Function backward substitution(augmented matrix,n):
   x = array of zeroes with length n
   for i = n-1 to 0:
       if augmented matrix[i, i] == 0:
              return "System has no unique solution."
       x[i] = augmented_matrix[i, n] / augmented_matrix[i, i]
       Update augmented_matrix for rows above the pivot
   return x, augmented_matrix
# The methods
Function Gauss_Elimination(A, B):
 n = number of rows of B
 augmented matrix = append B as last column to A
 augmented_matrix = forward_Elimination(augmented_matrix, n)
 x, augmented_matrix = backward_substitution(augmented_matrix, n)
 return x, augmented_matrix
Function Gauss_Jordan_Elimination(A, B):
 augmented_matrix = append B as last column to A
 augmented_matrix = forward_Elimination(augmented_matrix, n)
 augmented_matrix = backward_Elimination(augmented_matrix, n)
 x = last column of augmented_matrix
 return x, augmented matrix
Function Jacobi(self, A: np.ndarray, b: np.ndarray, epsilon=1e-9, iterations=50,
```

'mode' is what determines wether to use iterations or epsilon for solving # 'mode' = 1 is iterations, 'mode' = 2 is epsilon (absolute relative error) # if 'mode' is negative it means Gauess Seidel is applied and not Jacobi

x=None, mode=2):

```
max its = 2000
      GaussSeidel = False
     if (mode < 0):
       GaussSeidel = True
       mode = abs(mode)
     if (mode != 1 and mode != 2):
        print("Unknown Mode choosen in Jacobi.")
     if (x is None):
       x = zeroes with length rows of A
      D = diagonal of A
     if an element in D is 0
       print("Matrix contains zero diagonal elements, Jacobi method cannot
proceed.")
     curr_it = 0
     while (True):
       x_new = x.copy()
       for each row i A:
         x_new[i] = b[i]
         for each column j in A:
           if (i == i):
             continue
           if (GaussSeidel):
             x_new[i] -= A[i][j] * x_new[j]
           else:
             x_new[i] -= A[i][j] * x[j]
         x_new[i] /= A[i][i]
       if (mode == 1):
         if (curr_it > iterations):
           return x_new, curr_it-1
         if (curr_it > max_its or there's an overflow):
           if (GaussSeidel): print("Divergence occured in Gauss Seidel")
           else: print("Divergence occured in Jacobi")
           return x_new, curr_it-1
        else if (mode == 2):
          condition = True
```

```
if (not (absolute(x[i] - x_new[i]) < epsilon)):
             condition = False
         if (condition):
           return x_new, curr_it-1
         if (curr_it > max_its or there's an overflow):
           if (GaussSeidel): print("Divergence occured in Gauss Seidel")
           else: print("Divergence occured in Jacobi")
           return x_new, curr_it-1
       x = x_new
       curr it += 1
Function GaussSeidelA, b, epsilon=1e-9, iterations=50, x=None, mode=2):
   return Jacobi(A, b, epsilon, iterations, x, mode = -mode)
Function LUCroutsForm(A, B):
   L = zeroes matrix with same size of A
   U = zeroes matrix with same size of A
   L_and_U = zeroes matrix with same size of A
   n = number of rows of B
     for i=0 to n-1:
       for j=0 to n-1:
         L[i][j] = A[i][j]
         A[i] -= L[i][j] * U[j]
       L[i][i] = A[i][i] #i==i (diagonal)
       if L[i][i] != 0:
         U[i] = A[i] / L[i][i]
       else: # infinite number of solution or no solution
         return "System has no unique solution or no solution."
     #solve the equation
      augmented_L = add column B to L
     Y, augmented_L = forward_substitution(augmented_L,n)
      augmented_U = add column Y to U
     X, augmented_U = backward_substitution(augmented_U,n)
     for i=0 to n-1:
```

for each row i in A:

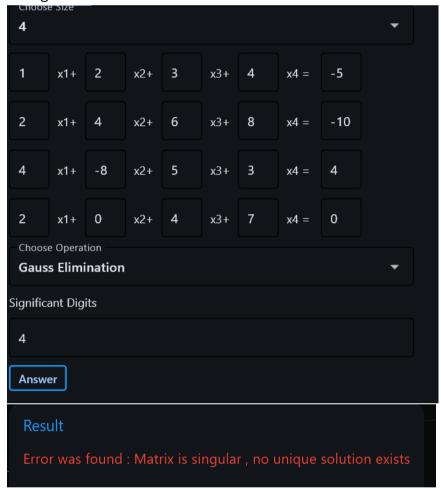
```
for j=0 to n-1:
           if i \le j:
             L_and_U[i][j] = U[i][j]
           else:
             L_and_U[i][j] = L[i][j]
     return X, L_and_U
Function LUCholeskyForm(A, B):
   L = zeroes matrix with same size of A
   If matrix A isn't positive definite:
Print("Error")
       return
     for i=0 to n-1:
       Update L matrix using Cholesky method
     U= Transpose of L #U = L transpose
     n=number of rows of B
     #solve the equation
     augmented L = add column b to L
     Y, augmented_L = forward_substitution(augmented_L,n)
     augmented_U = add column Y to U
     X, augmented_U = backward_substitution(augmented_U,n)
     return X,L
Function LUDoolittlesForm(A, B):
   L = zeroes matrix with same size of A
   U = zeroes matrix with same size of A
   L_and_U = zeroes matrix with same size of A
   n = number of rows of B
     for i=0 to n-1:
       L[i][i] = 1
       # Compute Upper Triangular Matrix
       for j=i to n-1:
          sum = 0
         for k=0 to i-1:
sum += L[i][k] * U[k][j]
          U[i][j] = A[i][j] - sum
       if U[i, i] == 0:
```

```
return "Matrix is singular, no unique solution."
```

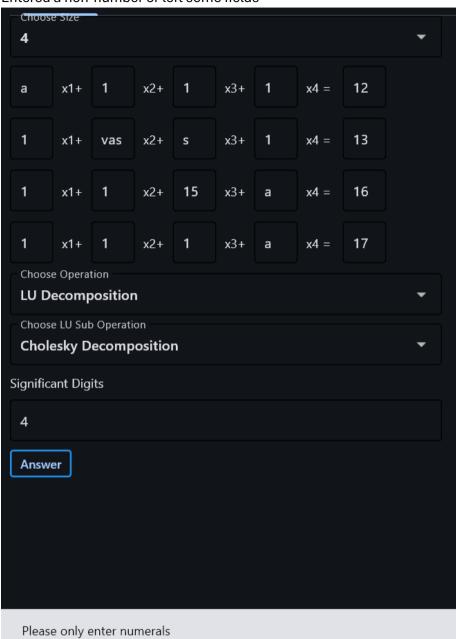
```
# Compute Lower Triangular Matrix
  for j=i+1 to n-1:
    sum = 0
    for k=0 to i-1:
 sum += L[j][k] * U[k][i]
     L[j][i] = (A[j][i] - sum) / U[i][i]
# Storing L and U in one matrix
for i=0 to n-1:
  for j=0 to n-1:
    if i <= j:
      L_and_U[i][j] = U[i][j]
    else:
      L_and_U[i][j] = L[i][j]
#solve the equation
augmented_LB = add colomn B to L
Y, augmented_LB = forward_substitution(augmented_LB, n)
if isinstance(Y, str):
  return Y
else:
  augmented_UY = add coloumn Y to U
  X ,augmented_UY = backward_substitution(augmented_UY, n)
return X, L_and_U
```

2. Sample runs for each method:

- General Cases Independent of Method:
 - 1- A singular matrix will return an error



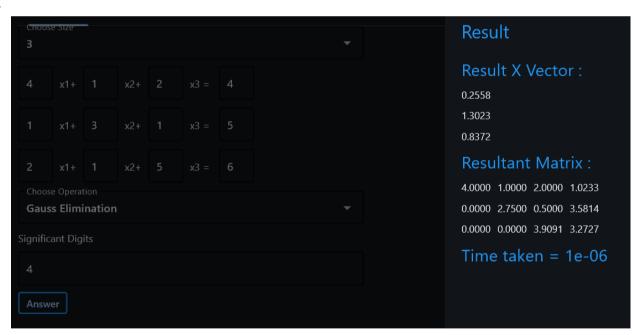
2- Entered a non-number or left some fields

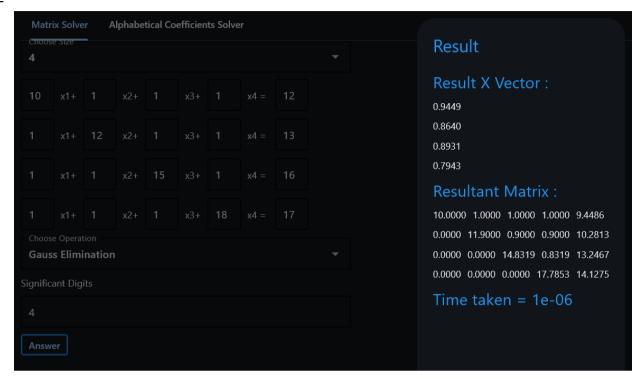


Gauss Elimination

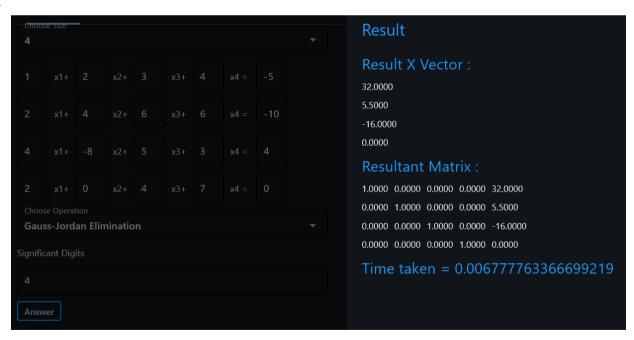
1-



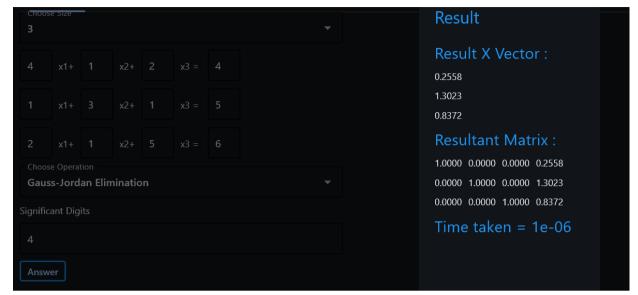


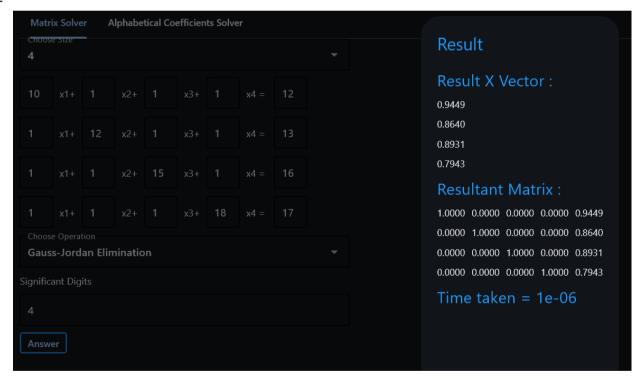


Gauss-Jordan



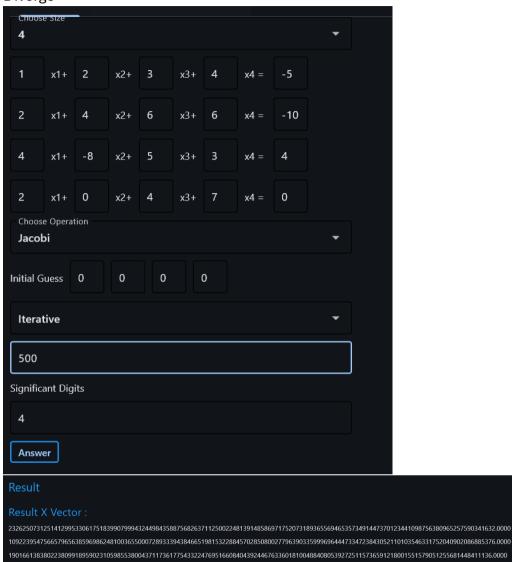
2-





Jacobi

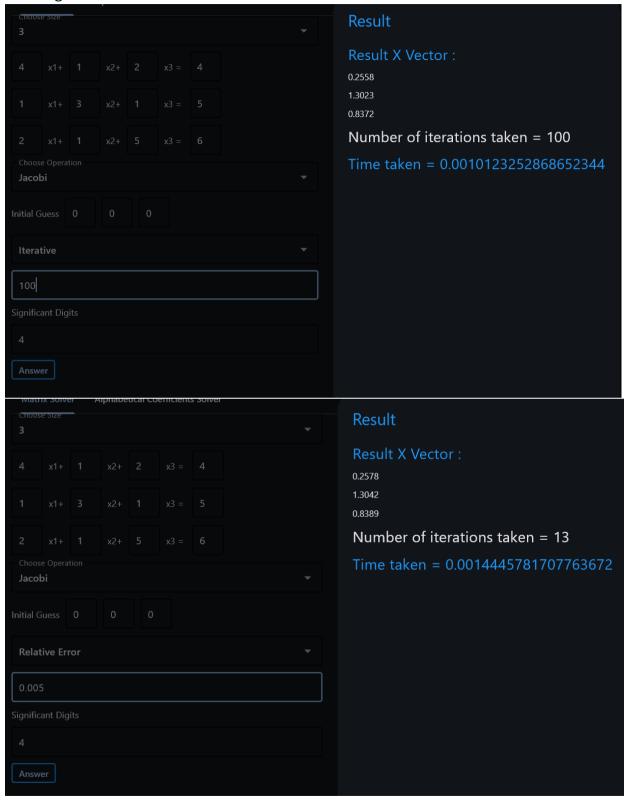
1- Diverge



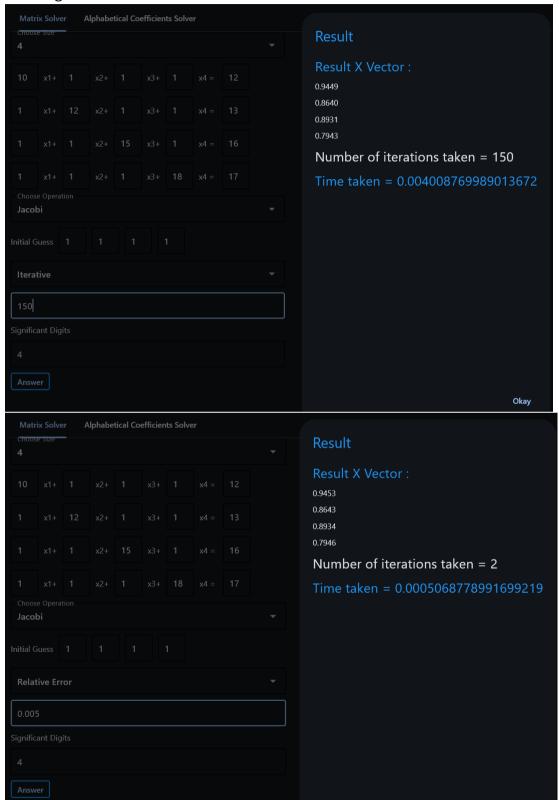
10922395475665796563859698624810036550007289333394384665198153228845702850800277963903359996964447334723843052110103546331752040902086885376.0000190166138380223809918959023105985538004371173617754332247695166084043924467633601810048840805392725115736591218001551579051255681448411136.0000409497900597073040922091934541855879499970017694585734734532109698696438170333168383123961769923161134351064396470307356790185191683391488.0000

Number of iterations taken = 500

2- Converge

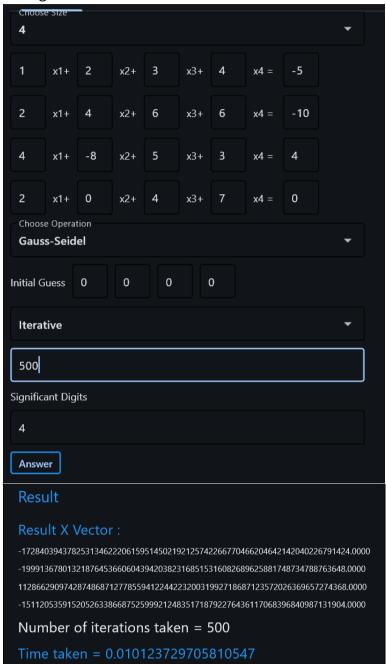


3- Converge

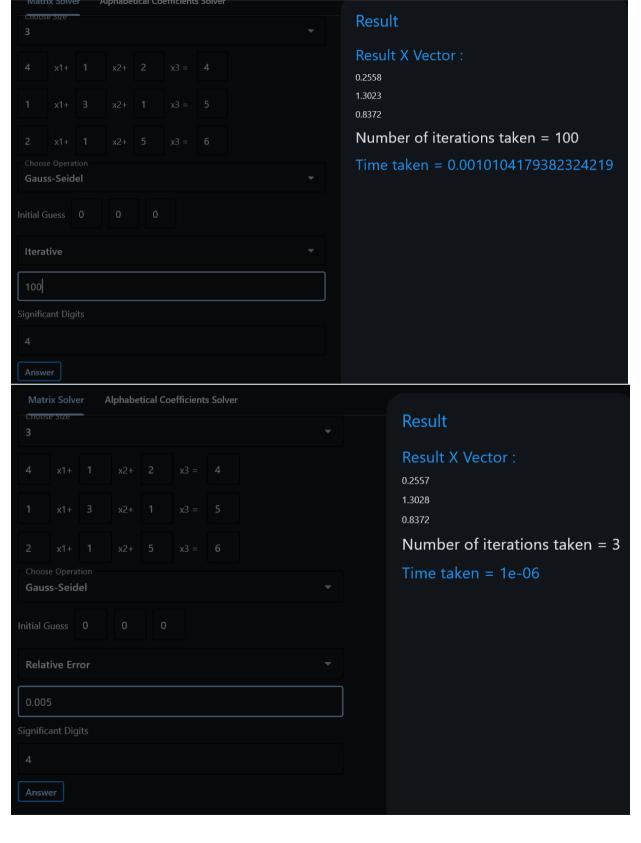


Gauss-Seidel

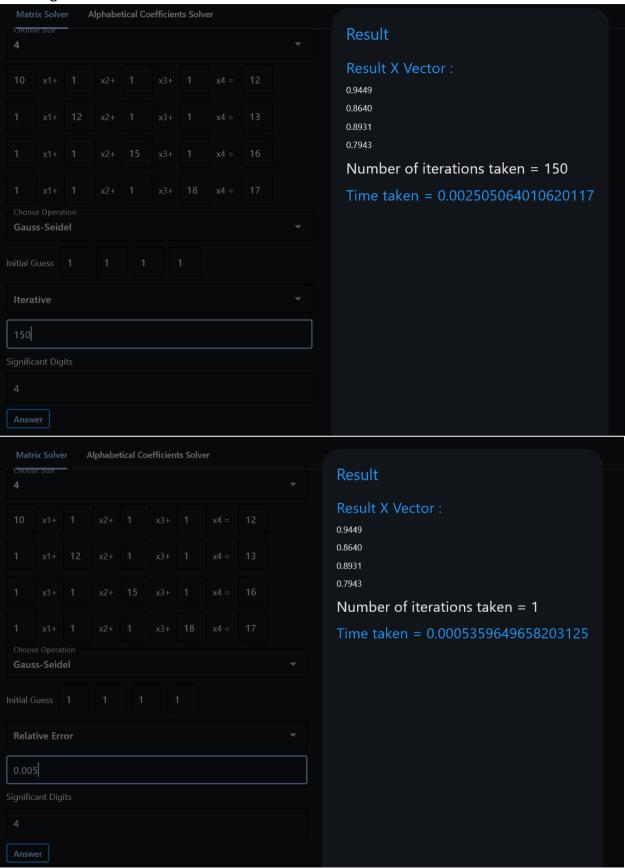
1- Diverge



2- Converge



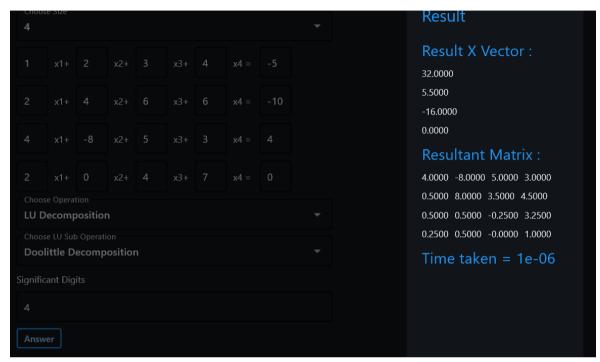
3- Converge

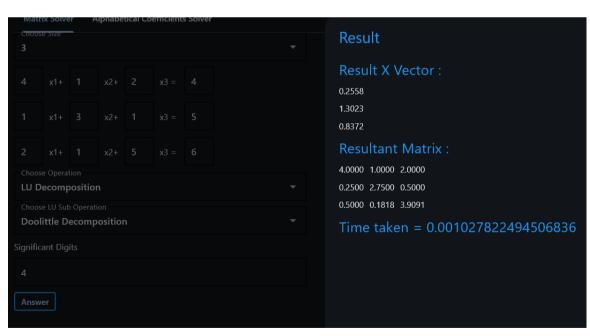


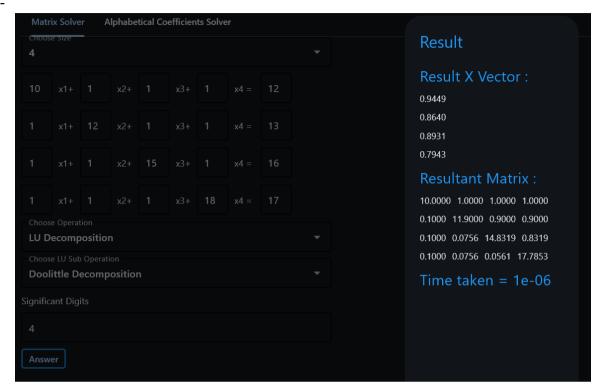
LU Decomposition

Doolittle

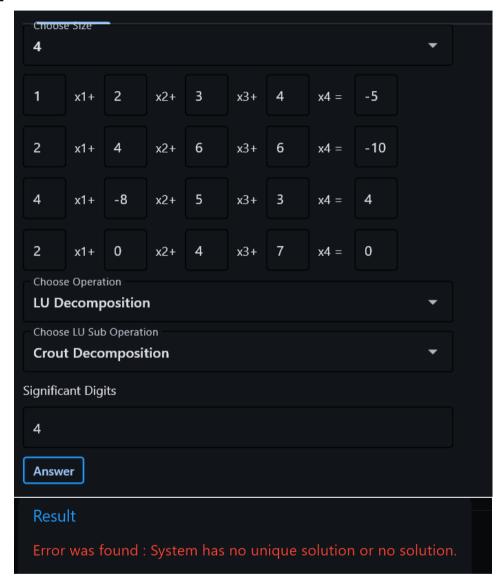
1-



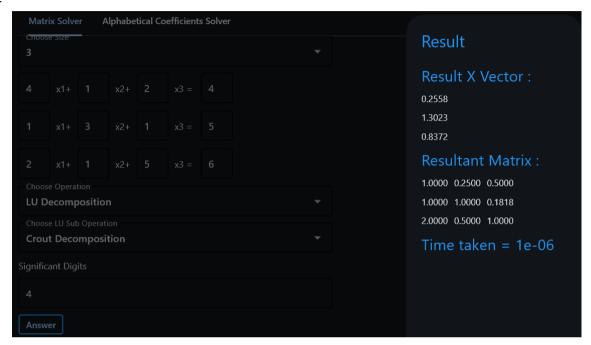


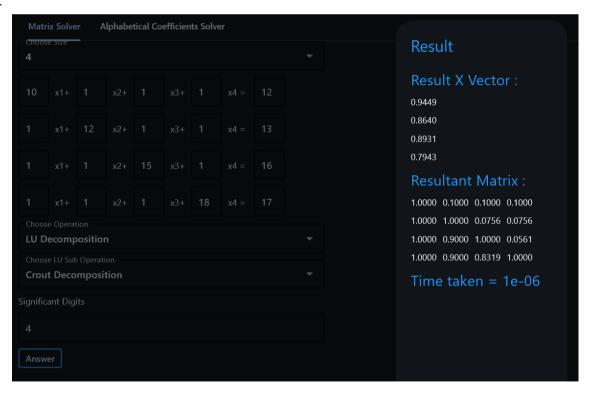


> Crout



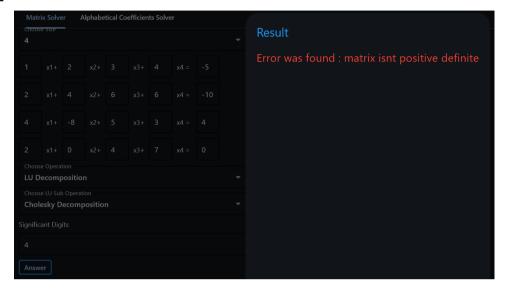
2-

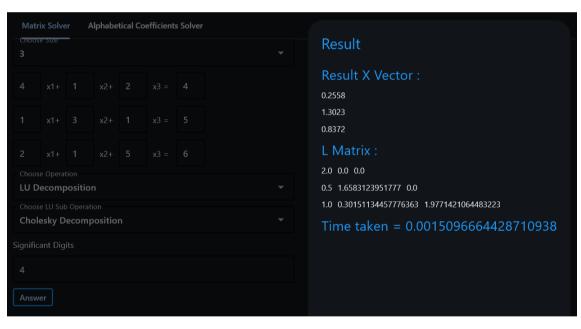




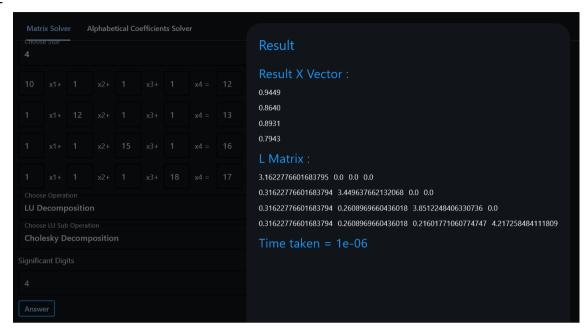
Cholesky

1-



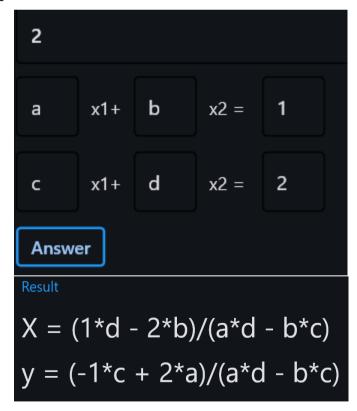


3-

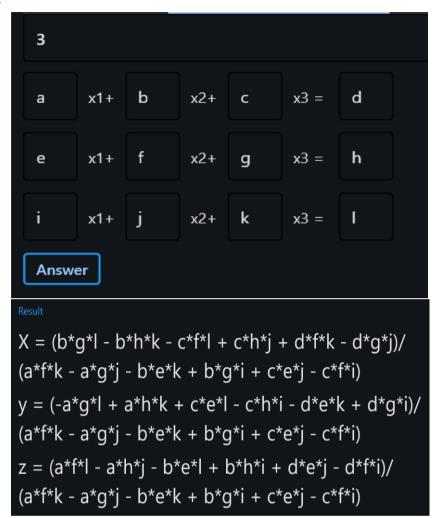


Bonus: Coefficients can be letters

1_



2-



3. Comparison between different methods (time complexity, convergence, best and approximate errors):

Method	Time Complexity	Convergence	Error
Gauss Elimination	O(n ³)	Direct method, no convergence issue	Numerical errors for ill- conditioned matrices
Gauss-Jordan	O(n ³)	Direct method, no convergence issue	Numerical errors for ill- conditioned matrices
Jacobi	O(n ²) / Iteration	Converges for diagonally dominant or	Slower convergence than Gauss- Seidel

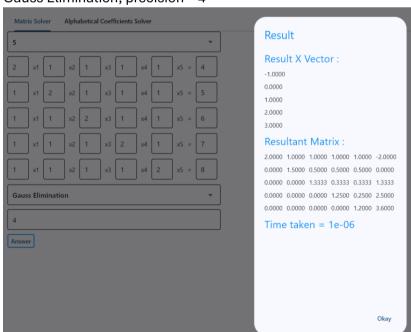
		positive-definite matrices	
Gauss-Seidel	O(n²) / Iteration	Converges for diagonally dominant or positive-definite matrices	Error decreases with each iteration
LU Decomposition	O(n ³)	Converges for non-singular matrices	Sensitive to ill- conditioned matrices

4. Data structures used:

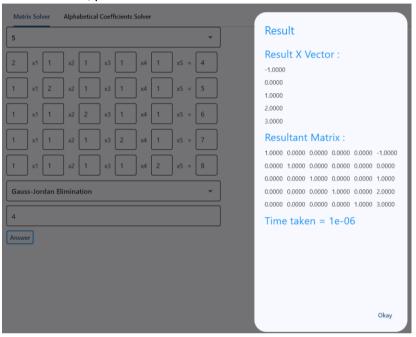
- 1D Lists (Arrays)
- 2D Lists (Matrices)
- Temporary (Scalar) variables
- Flags (Booleans)
- Indices

5. Test cases:

- ♣ 1st case
 - Gauss Elimination, precision = 4

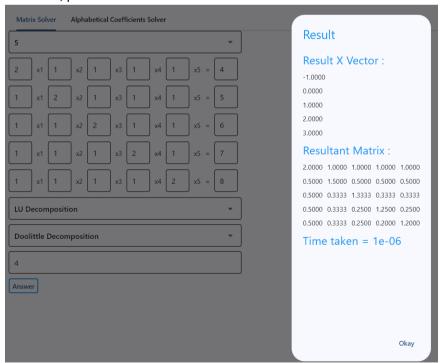


➤ Gauss Jordan, precision = 4

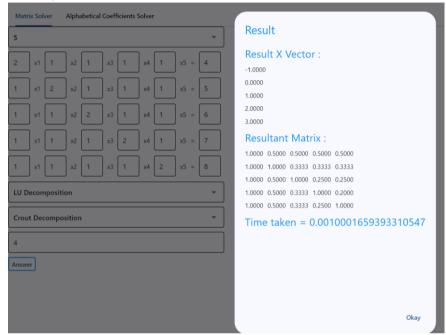


> LU decomposition

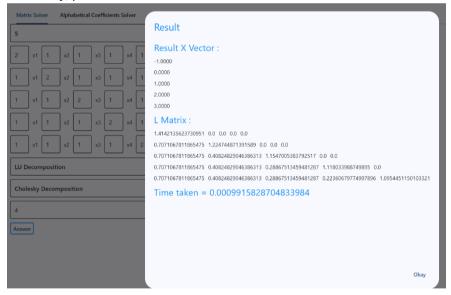
■ Doolittle, precision = 4



Crout, precision = 4

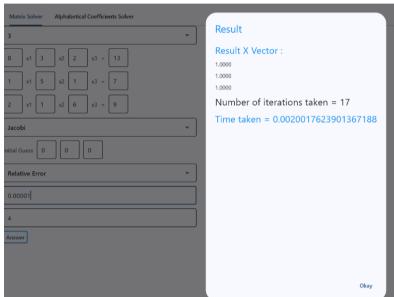


Cholesky, precision = 4

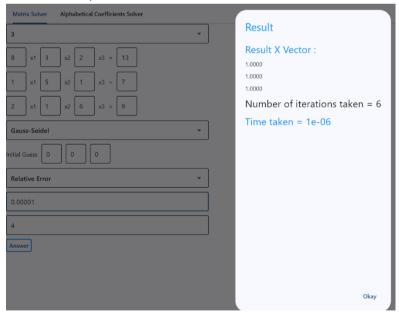


❖ 2nd case

➤ Jacobi, absolute relative error = 0.00001

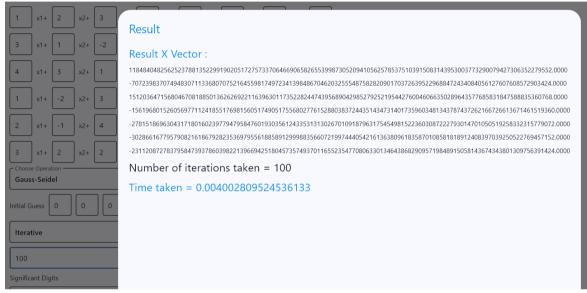


> Gauss Seidel, absolute relative error = 0.00001



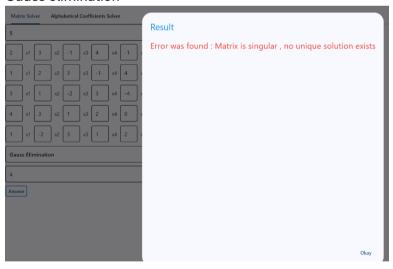
❖ 3rd case

Gauss Seidel, number of iterations = 100



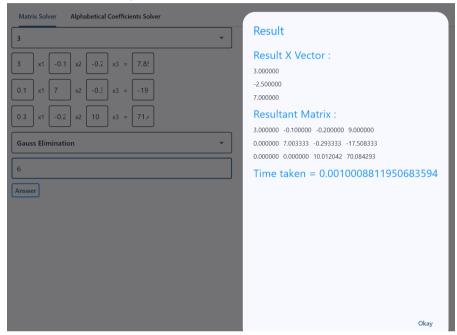
❖ 4th case

Gauss elimination

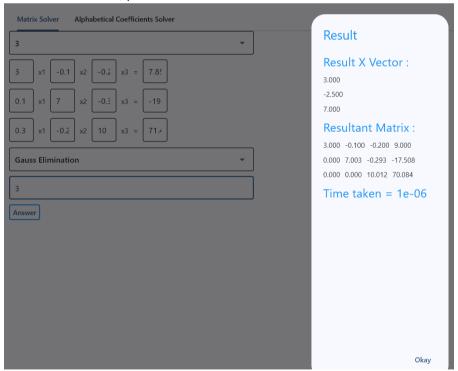


❖ 5th case

> Gauss Elimination, precision = 6

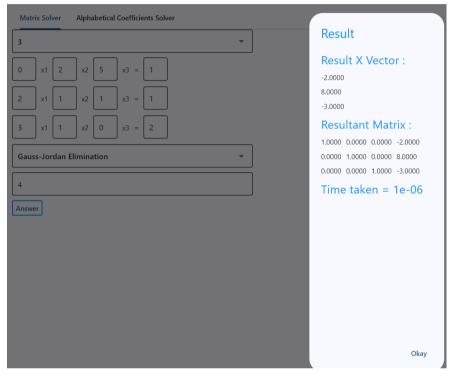


> Gauss Elimination, precision = 3



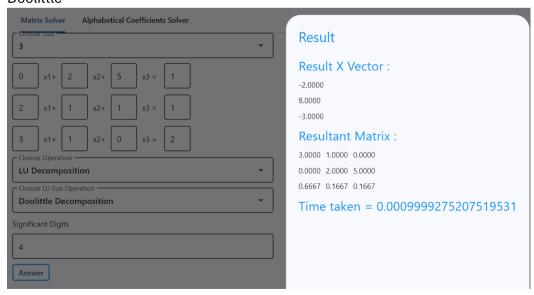
♦ 6th case

Gauss Jordan



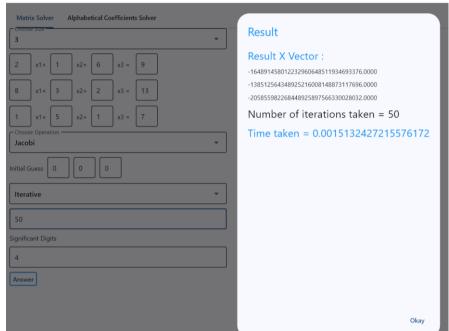
> LU Decomposition

Doolittle

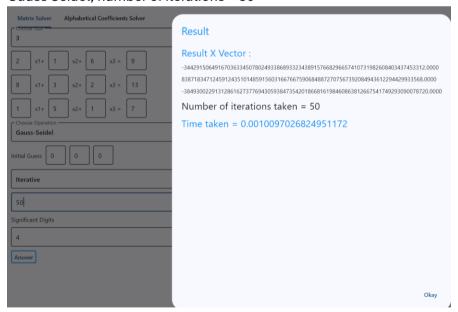


❖ 7th case

Jacobi, number of iterations = 50



Gauss Seidel, number of iterations = 50



6. Bonus:

Coefficients can be letters and the output is expressed in term of the letters: Suitable for system of equations of 2 or 3 variables. Any number of variables bigger than that is too much load for the computer.

Notes:

- 1- To run the app, open "RUN ME FOR PROJECT.exe"
- 2- You may need to install some python libraries Run the following in a terminal:

pip install flask flask-cors numpy sympy