COMPENG 3SK3: Computer-Aided Engineering Assignment #2: Gauss Elimination

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As a future member of the engineering profession, the student is responsible for performing the required work in an honest manner, without plagiarism and cheating. Submitting this work with my name and student number is a statement and understanding that this work is my own and adheres to the Academic Integrity Policy of McMaster University and the Code of Conduct of the Professional Engineers of Ontario. Submitted by [Lelna Gwet, gwetl, 400060749]

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Part 1:

See Appendix and attached Matlab files for complete code of GaussElimination() and GaussElimination_Pivoting() functions.

Part 2: Implementation

1. Using the built-in matlab function, rand(), random coefficient matrices and right-hand side vectors were generated for test cases.

```
% Part II: Question 1
function [A_mat, b_vec] = random_test_case(n)
    A_mat = 200*rand(n)-100
    b_vec = 200*rand(n, 1)-100
end
```

Figure 1: Matlab function: random_test_case(n)

Rand(n) generates an $n \times n$ matrix with random floating-point digits between 0 and 1.0. By multiplying rand(n) by 200 and subtracting 100, a coefficient matrix with dimensions $n \times n$ is generated, with digits in the prescribed range (-100.0, 100). Similarly, Rand(n, 1) generates an nx1 column vector with random floating-point digits between 0 and 1.0. By multiplying rand(n, 1) by 200 and subtracting 100, a right-hand side vector with dimensions $n \times n$ is generated, with digits in the prescribed range (-100.0, 100).

2. (See Appendix A and attached Matlab files for complete implementation code).

A function, <code>check_matrix_solution()</code>, takes a coefficient matrix, solution vector, and right-hand side vector and checks that the solution vector is correct by multiplying the solution vector with the coefficient matrix and comparing that resultant right-hand side vector with the right-hand side vector taken by the function.

```
function areEqual = check_matrix_solution(A_mat, b_vec, solution_mat)
    %checking that b_vec are equal

    %create an nx1 matrix to store if they're equal
    areEqual = zeros(height(b_vec), 1);

    solved_b_vec = A_mat*solution_mat;

    for i = 1:height(b_vec)
        %define a tolerance|
        tol = 5*eps(b_vec(1));
        areEqual(i) = abs(solved_b_vec(i)-b_vec(i))<tol;
    end
end</pre>
```

Figure 2: Matlab function: check_matrix_solution(A_mat, b_vec, solution_mat)

To check that both right-hand side vectors are equivalent, each element in both vectors are compared individually. Since the values in both vectors are floating point digits, it can be difficult for them to be *exactly* equivalent for all decimal places in its precision. Rather than checking for equivalency with the logic equivalence, '=', the elements are first subtracted from each other. In theory, when two numbers are equivalent, the result of subtracting them would be zero. However, because these are floating point numbers that are not *exactly* equivalent, a tolerance, or very small number, is defined to quantify how "different" each number can be before they are considered different numbers (i.e. not equivalent). If the result of subtracting both values is less than the defined tolerance, then they are considered equivalent. Otherwise, they are considered not equivalent. The result of each element's equivalence is stored in a vector called, areEqual(). If the areEqual() vector is all 1's, then the right-hand side vectors are equal.

				solution_mat =	
				-2.7716	
A_mat =				-3.0339	
				-0.17825	
				-1.5594	
95.649	-87.428	-27.316	30.498		
2.6442	-44.751	-95.367	71.847	V	
70.41	-41.891	-53.224	-21.443	X =	
47.802	-70.274	-58.623	29.467	-2.7716	
				-3.0339	
				-0.17825	
				-1.5594	
b_vec =					
40 545				checked =	
-42.547					
33.4				1	
-25.13				1	
45.214				1	
10.211				1	

Figure 3: example of 4x4 matrix using check_matrix_solution(A_mat, b_vec, solution_mat)

Additionally, the Matlab built-in linear equation solver, linsolve(), was also used to verify the solution. For the 2x2, 3x3, and 4x4 systems tested, the answer from built-in solver appears to be consistently correct.

3. (See Appendix B and attached Matlab files for complete implementation code).



Figure 4a: Plotting points for Running time vs Matrix dimension, n.

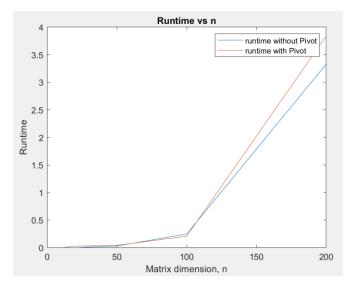


Figure 4b: Plot of Running time vs Matrix dimension, n.

As per Figure 4a, the running times for solving five randomly generated matrices of different sizes (n = 10, 20, 50, 100, 200) with the Gauss_Elimination() function were, respectively, recorded and stored in a $5 \times I$ row vector, tEnd_av. Each matrix size's running time was repeated 10 times and an average of the 10 iterations was stored. The same procedure was repeated for the Gauss_Elimination_Pivoting() function

and stored into the 5×1 row vector, tEnd_av2. The resulting vectors were plotted on the 'Runtime vs n' graph shown in Figure 4. Upon observing the resulting graph, it does appear to support the theoretical result that the running time on an $n \times n$ system is proportional to n^3 . Though it is important to keep in mind that it is rare for a matrix to require pivoting and running times can also vary significantly within the same matrix size, a general trend was still observed between the running times required for an $n \times n$ matrix when using Gauss_Elimination() vs Gauss_Eliminiation_Pivoting(). In general, Gauss_Elimination_Pivoting() function tends to require slightly more running time to solve the same size matrix. At the worst case, based in the above example, it appears that adding pivoting to the Gauss Elimination algorithm adds ~15% of overhead time; which may prove to be significant at larger systems (i.e., n = 1000).

4. (See Appendix C and attached Matlab files for complete implementation code).

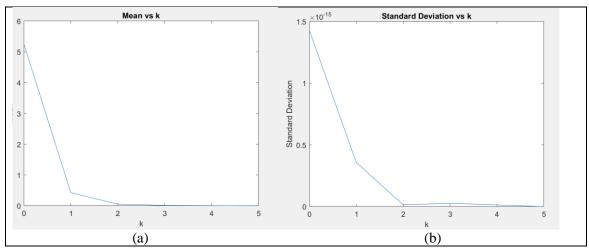


Figure 5: (a) Mean vs k plot; (b) Standard Deviation vs k plot.

An element of error, ranging from the order of ± 1.0 , was introduced to 100 randomly generated 10×10 matrices. To observe the effects of the error, for each 10×10 matrix, the difference between each element of the original system solution and the perturbed system solution was taken, squared, and summed. The square root of the result of this operation is then taken, resulting in the total error between the system solutions. The total error of each 10×10 system (out of the total 100 systems) is stored into the first column of a 100×5 matrix, errors_stored. Once all the errors have been computed for all 100 systems, the mean is calculated by the following definition:

$$Mean = \frac{\sum_{i=1}^{100} (total \ system \ errors)_{i}}{total \ # \ of \ system \ errors}$$

Similarly, the standard deviation is calculated by following the following definition:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{100} \left(\text{ (total system error)}_{i} - \text{mean} \right)^{2}}{\text{ (total # of systems)} - 1}}$$

This procedure was repeated with the following elements of error added: [-0.1, 0.1], [-0.01, 0.01], [-0.001, 0.001], [-0.00001, 0.00001]. Figure 5 represents a plot of the mean (5a) and standard deviation (5b) depending on the order of error introduced to a system, where k is from [-10^k, 10^{-k}]. As per the plot data,

it can be observed that as the order of the added error decreases, the mean and standard deviation also decreases in a cubic manner.

Appendix A: Question 2 Implementation.

```
format short g
% testing Part II: Question 1
% random test case(6)
%Part II: Question 2
% WITHOUT PIVOTING
[A mat, b vec] = random test case(2);
solution mat = Gauss Elimination(A mat, b vec)
X = linsolve(A mat, b vec)
checked = check matrix solution(A mat, b vec, solution mat)
[A mat, b vec] = random test case(3);
solution mat = Gauss Elimination(A mat, b vec)
checked = check matrix solution(A mat, b vec, solution mat)
X = linsolve(A mat, b vec)
[A mat, b vec] = random test case(4)
solution mat = Gauss Elimination (A mat, b vec)
checked = check matrix solution(A mat, b vec, solution mat)
X = linsolve(A mat, b vec)
% WITH PIVOTING [A mat, b vec] = random test case(2);
solution mat = Gauss Elimination Pivoting(A mat, b vec)
X = linsolve(A mat, b vec)
checked = check_matrix_solution(A_mat, b_vec, solution_mat)
[A_mat, b_vec] = random_test_case(3);
solution mat = Gauss Elimination Pivoting(A mat, b vec)
X = linsolve(A mat, b vec)
checked = check matrix solution(A mat, b vec, solution mat)
```

```
[A_mat, b_vec] = random_test_case(4);
solution_mat = Gauss_Elimination_Pivoting(A_mat, b_vec)
X = linsolve(A_mat, b_vec)
checked = check_matrix_solution(A_mat, b_vec, solution_mat)
```

Appendix B: Question 3 Implementation.

```
format short g
n = [10, 20, 50, 100, 200];
tEnd = zeros(1, 10);
tEnd av = zeros(1, 5);
for i = 1:5
      for j = 1:10
            [A mat, b vec] = random test case(n(1, i));
            TStart = tic;
            solution mat = Gauss Elimination(A mat, b vec);
            tEnd(j) = toc(TStart);
      end
      tEnd av(i) = sum(tEnd)/height(tEnd);
end
tEnd av
plot(n, tEnd av)
hold on
n = [10, 20, 50, 100, 200];
tEnd = zeros(1, 10);
tEnd av2 = zeros(1, 5);
for i = 1:5
      for j = 1:10
      [A_mat, b_vec] = random_test_case(n(1, i));
      TStart = tic;
      solution_mat = Gauss_Elimination_Pivoting(A_mat, b_vec);
      tEnd(j) = toc(TStart);
      end
      tEnd_av2(i) = sum(tEnd)/height(tEnd);
end
tEnd av2
```

```
plot(n, tEnd_av2)
title('Runtime vs n')
xlabel('Matrix dimension, n')
ylabel('Runtime')
legend('runtime without Pivot', 'runtime with Pivot')
hold off
```

Appendix C: Question 4 Implementation.

```
format short q
%Part II: Question 4
%-----FIRST: [-1.0, 1.0]------
% create a column vector to store the 100 error values
errors stored = zeros(100, 5);
variance = zeros (1, 5);
std dev = zeros (1, 5);
% generate 100 random 10 x 10 systems
n = 10;
for i = 1:100
     [A mat, b vec] = random test case(n);
     %record solution to system
     solution mat = Gauss Elimination(A mat, b vec)
     % "perturb system" --> add a number -1.0 to 1.0 to each element in
     % A mat and b vec
     %generate 10 by 10 matrix with numbers -1.0 to 1.0 and add it to A mat
     A mat perturbed = A mat+ (2*rand(n)-1);
     b vec perturbed = b vec + (2*rand(n, 1)-1);
     perturbed solution mat = Gauss Elimination (A mat perturbed,
     b vec perturbed)
     error matrix = (solution mat-perturbed solution mat).^2;
     sum error = sum(error matrix);
     error = sqrt(sum_error)
     errors stored(i, 1) = error;
end
for i = 1:100
   [A mat, b vec] = random test case(n);
```

```
%record solution to system
   solution mat = Gauss Elimination(A mat, b vec)
    % "perturb system" --> add a number -1.0 to 1.0 to each element in
    % A mat and b vec
    %generate 10 by 10 matrix with numbers -1.0 to 1.0 and add it to A mat
   A mat perturbed = A mat+ (0.2*rand(n)-0.1);
   b vec perturbed = b vec + (0.2*rand(n, 1)-0.1);
   perturbed solution mat = Gauss Elimination(A mat perturbed,
b vec perturbed)
   error matrix = (solution mat-perturbed solution mat).^2;
   sum error = sum(error matrix);
   error = sqrt(sum error)
   errors stored(i, 2) = error;
end
%-----THIRD: [-0.01, 0.01]-----
for i = 1:100
    [A mat, b vec] = random test case(n);
   %record solution to system
    solution mat = Gauss Elimination(A mat, b vec)
    % "perturb system" --> add a number -1.0 to 1.0 to each element in
    % A mat and b_vec
   %generate 10 by 10 matrix with numbers -1.0 to 1.0 and add it to A mat
   A mat perturbed = A mat+ (0.02*rand(n)-0.01);
   b vec perturbed = b vec + (0.02*rand(n, 1)-0.01);
   perturbed solution mat = Gauss Elimination(A mat perturbed,
b vec perturbed)
```

```
error matrix = (solution mat-perturbed solution mat).^2;
   sum error = sum(error matrix);
   error = sqrt(sum error)
   errors stored(i, 3) = error;
end
for i = 1:100
   [A mat, b vec] = random test case(n);
   %record solution to system
   solution mat = Gauss Elimination(A mat, b vec)
   % "perturb system" --> add a number -1.0 to 1.0 to each element in
   % A mat and b vec
   %generate 10 by 10 matrix with numbers -1.0 to 1.0 and add it to A mat
   A_{mat\_perturbed} = A_{mat+} (0.002*rand(n)-0.001);
   b vec perturbed = b vec + (0.002*rand(n, 1)-0.001);
   perturbed solution mat = Gauss Elimination(A mat perturbed,
b vec perturbed)
   error matrix = (solution mat-perturbed solution mat).^2;
   sum error = sum(error matrix);
   error = sqrt(sum error)
   errors stored(i, 4) = error;
end
for i = 1:100
   [A mat, b vec] = random test case(n);
   %record solution to system
   solution mat = Gauss Elimination(A mat, b vec)
```

```
% "perturb system" --> add a number -1.0 to 1.0 to each element in
    % A mat and b vec
    %generate 10 by 10 matrix with numbers -1.0 to 1.0 and add it to A mat
    A mat perturbed = A mat+ (0.00002*rand(n)-0.00001);
    b vec perturbed = b vec + (0.00002*rand(n, 1)-0.00001);
    perturbed solution mat = Gauss Elimination(A mat perturbed,
b vec perturbed)
    error matrix = (solution mat-perturbed solution mat).^2;
    sum error = sum(error matrix);
    error = sqrt(sum error)
    errors stored(i, 5) = error;
end
mean = sum(errors stored)./height(errors stored)
for i=1:5
    variance(i) = (sum(errors stored(:, i) -
mean(i)).^2)/(height(errors stored)-1);
    std dev(i) = sqrt(variance(i));
end
std dev
% PLOTS
% mean vs k
% std dev vs k
% k = 0 1 2 3 5
k = [0, 1, 2, 3, 5]
height (errors stored)
errors stored
```

```
figure(1)
plot(k, mean)
figure(2)
plot(k, std_dev)
```