



# MATH7003-00: Assignment #9

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## Problem.

#1. Prove the inequality (8.5.13) on slide 5 of week11 [1].

$$\|x - x^{(m+1)}\|_{\infty} \leq \frac{c}{1-c} \|x^{(m+1)} - x^{(m)}\|_{\infty}.$$

#2. Consider the example on slide 18 and write down m-files for Gauss-Seidel and SOR. Generate Table 8.9. Discuss about the result. [1].

*Example.* Solve

$$\frac{\partial^2 u}{\partial x^2} + \frac{\partial^2 u}{\partial y^2} = 0 \quad 0 \leq x, y \leq 1$$

$$u(0, y) = \cos(\pi y), \quad u(1, y) = e^{\pi} \cos(\pi y), \quad u(x, 0) = e^{\pi x}, \quad u(x, 1) = -e^{\pi x}.$$

The true solution is

$$u(x, y) = e^{\pi x} \cos(\pi y).$$

*Example.* Recall the previous example (8.8.11). This was solved with both the Gauss-Seidel method and the SOR method. The initial guess for the iteration was taken to be the "bilinear" interpolation formula for the boundary data  $f$ :

$$\begin{aligned} u_h^{(0)}(x, y) &= (1-x)f(0, y) + xf(1, y) + (1-y)f(x, 0) + yf(x, 1) \\ &\quad - [(1-y)(1-x)f(0, 0) + (1-y)xf(1, 0) + y(1-x)f(0, 1) + xyf(1, 1)] \end{aligned}$$

at all interior grid points. The error test to stop the iteration was

$$\max_{1 \leq j, k \leq N-1} |u_h(x_j, y_k) - u_h^{(m)}(x_j, y_k)| \leq \epsilon$$

with  $\epsilon > 0$  given and the right-hand side of (8.7.5) used to predict the error in the iterate. The numerical results for the necessary number of iterates are given in **Table 8.9**.

**Solution. (problem #1)**

For the initial guess  $x^{(0)}$ , we know the fact that  $x^{(1)} - x^{(0)} = Cr^{(0)}$  where  $r^{(0)} = b - Ax^{(0)}$ ,  $C$  is the approximation of  $A^{-1}$ . Then, in general, we can define this form recursively, and we obtain a recursion formula for the error as

$$\begin{aligned} Cx - x^{(m+1)} &= x - x^{(m)} - Cr^{(m)} = x - x^{(m)} - C[b - Ax^{(m)}] \\ &= x - x^{(m)} - C[Ax - Ax^{(m)}] \end{aligned}$$

Thus,  $x - x^{(m+1)} = (I - CA)(x - x^{(m)})$ . By induction, we also obtain  $x - x^{(m)} = (I - CA)^m(x - x^{(0)})$  for  $m \geq 0$ . In this, if we assume  $\|I - CA\| < 1$  for some matrix norm, then

$$\|x - x^{(m)}\| = \|I - CA\|^m \|x - x^{(0)}\|$$

and, this converges to zero as  $m \rightarrow \infty$  for any choice of initial guess  $x^{(0)}$ . This implies that

$$(I - CA)^m \rightarrow 0 \text{ as } m \rightarrow \infty.$$

Now, note that the theorem and the definition.

**Theorem 7.9** Let  $A$  be a square matrix of order  $n$ . Then  $A^m$  converges to the zero matrix as  $m \rightarrow \infty$  if and only if  $r_\sigma(A) < 1$ .

**Definition** Let  $A$  be an arbitrary matrix. The **spectrum** of  $A$  is the set of all eigenvalues of  $A$ , and it is denoted by  $\sigma(A)$ . The **spectral radius** is the maximum size of these eigenvalues, and it is denoted by

$$r_\sigma(A) = \max_{\lambda \in \sigma(A)} |\lambda|$$

Then, by Theorem 7.9, this is equivalent to  $r_\sigma(I - CA) < 1$ . For the case of  $I - AC$ , we obtain

$$I - AC = A(I - CA)A^{-1}$$

and thus  $I - AC$  and  $I - CA$  are similar matrices and have the same eigenvalues, by the **diagonalization theorem**. (see Chapter 5 in [4]) So if  $\|I - AC\| < 1$ , then  $r_\sigma(I - CA) < 1$  is true, even if  $\|I - CA\| < 1$  is not true, and convergence will still occur.

Therefore,  $x - x^{(m+1)} = (I - CA)(x - x^{(m)})$  shows that the rate of convergence of  $x^{(m)}$  to  $x$  is linear:

$$\|x - x^{(m+1)}\| \leq c \|x - x^{(m)}\| \text{ for } m \geq 0, \text{ with } c < 1 \text{ unknown.}$$

And,  $c$  is estimated computationally with

$$c = \max \frac{\|x^{(m+2)} - x^{(m+1)}\|}{\|x^{(m+1)} - x^{(m)}\|}.$$

Then, we now easily can produce an error bound that

$$\|x^{(m+1)} - x^{(m)}\| \geq \| [x - x^{(m)}] - [x - x^{(m+1)}] \| \dots \text{ (I)}$$

$$\geq \|x - x^{(m)}\| - \|x - x^{(m+1)}\| \dots \text{ (II)}$$

$$\geq \|x - x^{(m)}\| - c \|x - x^{(m)}\| \dots \text{ (III)}$$

(I) is  $x^{(m+1)} - x^{(m)} = x^{(m+1)} + (x - x) - x^{(m)} = [x^{(m+1)} - x] + [x - x^{(m)}] = [x - x^{(m)}] - [x - x^{(m+1)}]$ ,

(II) is by triangle inequality, and (III) is  $\|x - x^{(m+1)}\| \leq c \|x - x^{(m)}\|$ .

Thus, we obtain

$$\begin{aligned} \|x^{(m+1)} - x^{(m)}\| &\geq \|x - x^{(m)}\| - c \|x - x^{(m)}\| \\ &= (1 - c) \|x - x^{(m)}\| \end{aligned}$$

and, finally we have

$$\|x - x^{(m)}\| \leq \frac{1}{1 - c} \|x^{(m+1)} - x^{(m)}\| \Rightarrow \|x - x^{(m+1)}\| \leq \frac{c}{1 - c} \|x^{(m+1)} - x^{(m)}\|$$

since  $\|x - x^{(m+1)}\| \leq c \|x - x^{(m)}\| \Rightarrow c \|x - x^{(m)}\| \leq c \left( \frac{1}{1 - c} \|x^{(m+1)} - x^{(m)}\| \right)$ .

■

**Solution. (problem #2)**

For  $j = 1, 2, \dots, N-1$  and  $k = 1, 2, \dots, N-1$ , the ‘**matrix-free**’ form of the **Gauss-Seidel (G-S) method** of the given partial differential equation is as follows.

$$u_h^{(m+1)}(x_j, y_k) = \frac{1}{4} [u_h^{(m)}(x_{j+1}, y_k) + u_h^{(m)}(x_j, y_{k+1}) + u_h^{(m+1)}(x_{j-1}, y_k) + u_h^{(m+1)}(x_j, y_{k-1})].$$

For the boundary points, use

$$u_h^{(m)}(x_j, y_k) = f(x_j, y_k) \text{ for all } m \geq 0.$$

Since the equation of this example is the homogeneous equation,  $g(x_j, y_k) = 0$ . ( refer to (8.8.12) in [1] )  
Also, the **successive overrelaxation (SOR) method** is as follows.

$$v_h^{(m+1)}(x_j, y_k) = \frac{1}{4} [u_h^{(m)}(x_{j+1}, y_k) + u_h^{(m)}(x_j, y_{k+1}) + u_h^{(m+1)}(x_{j-1}, y_k) + u_h^{(m+1)}(x_j, y_{k-1})],$$

$$u_h^{(m+1)}(x_j, y_k) = \omega v_h^{(m+1)}(x_j, y_k) + (1 - \omega) u_h^{(m)}(x_j, y_k) \text{ for } j = 1, 2, \dots, N-1, \ k = 1, 2, \dots, N-1.$$

Note that the **optimal acceleration parameter** is

$$\omega^* = \frac{2}{1 + \sqrt{1 - \xi^2}} \text{ where } \xi = 1 - 2\sin^2\left(\frac{\pi}{2N}\right).$$

If  $\omega^* = 1$ , then the formula of SOR is directly equals to the fomular of Gauss-Seidel. i.e., we can easily know that the SOR method is the generalized version of Gauss-Seidel method.

We use the stop criterion in **problem #1** as

$$\|x - x^{(m+1)}\|_{\infty} \leq \frac{c}{1 - c} \|x^{(m+1)} - x^{(m)}\|_{\infty}, \quad \text{where } c \doteq \frac{\|x^{(m+1)} - x^{(m)}\|_{\infty}}{\|x^{(m)} - x^{(m-1)}\|_{\infty}},$$

in order for our implementation. Now, the results of **problem #2** is attached below. (see **Figure 1.**)

**Table 8.9 Number of iterates necessary to solve (8.8.5)**

$N$	$\epsilon$	Gauss-Seidel	SOR
8	.01	25	12
8	.001	40	16
16	.001	142	32
32	.001	495	65
8	.0001	54	18
16	.0001	201	35
32	.0001	733	71

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Table 8.9 Number of iterates necessary to solve (8.8.5)

N	epsilon	Gauss-Seidel	SOR
8	0.01	25	12
8	0.001	40	16
16	0.001	142	31
32	0.001	495	65
8	0.0001	54	16
16	0.0001	201	31
32	0.0001	733	65

f\_x >>

**Figure 1.** The results of the problem 2 using MATLAB. The left-side is in the textbook.

### Discussion. (problem #2)

Our problem has the equivalent step size  $h = 1/N$  for  $x$  and  $y$ . Hence the finite mesh grid depends on the step parameter  $N$ . This implies that if  $N$  is larger, then the iteration number is basically larger.

Moreover, if the stop criterion  $\epsilon > 0$  is smaller, we need to iterate more than previous, in order to meet more rigorous criterion  $\epsilon$ .

In Table 8.9., we suggest the Gauss-Seidel and SOR results for  $N = 8, 16, 32$  and  $\epsilon = 0.01, 0.001, 0.0001$ , and we can see that if  $N$  and  $\epsilon$  is larger, the iteration of both methods is larger.

Especially, we already learned the fact that the SOR method is the acceleration of Gauss-Seidel method, so we intuitively can see that the iteration number of SOR results are better than Gauss-Seidel results in Table 8.9. So we conclude that the use of SOR greatly reduces the resulting work, although it still is large when  $N$  is large.

With either method, note that doubling  $N$  will increase the number of equations to be solved by a factor of 4, and thus the work per iteration will increase by the same amount.

## Table\_8\_9\_HW9.m

```
%% MATH7003-00: Assignment #9, 2019310290 Sangman Jung.
clear,clc

N = [8 16 32]; % step N
epsilon = [0.01 0.001 0.0001]; % error criterion
f = @(x,y) exp(pi*x).*cos(pi*y); % exact solution of our problem

ksi = 1-2.*((sin(pi./(2*N))).^2);
omega = 2./(1+sqrt(1-(ksi).^2)); % optimal acceleration parameter

uval(length(N),length(epsilon),2) = []; % pre-allocation of the numerical solution

iteration = zeros(length(N),length(epsilon)); % pre-allocation of G-S iteration
iteration_sor = zeros(length(N),length(epsilon)); % pre-allocation of SOR iteration

% Full Loop
for w_iter = 1:2 % w_iter = 1 is G-S, w_iter = 2 is SOR
    for N_iter = 1:length(N) % iterate per step N
        h = 1/(N(N_iter)); % step size
        x = 0:h:1; y = x; % spatial variables (grid)
        nx = length(x); ny = length(y); % the size of the grid
        u_ini = zeros(nx,ny); % initial guess
        u_exact = zeros(nx,ny); % pre-allocation of exact solution
        u_new = zeros(nx,ny); % pre-allocation of numerical solution
        for eps_iter = 1:length(epsilon) % iteration of the criterion
            m_iter = 1; % initialize the iteration number
            for k = 1:ny
                for j = 1:nx
                    u_ini(j,k) = (1-x(j)) * f(0,y(k)) + x(j) * f(1,y(k)) + (1-y(k)) * f(x(j),0) + ...
                        y(k) * f(x(j),1) - (1-y(k)) * (1-x(j)) * f(0,0) + (1-y(k)) * x(j) * f(1,0) + ...
                        y(k) * (1-x(j)) * f(0,1) + x(j) * y(k) * f(1,1); % compute the initial guess
                    u_exact(j,k) = f(x(j),y(k)); % allocate the exact solution
                end
            end
            u_old = u_ini; % update the m-iteration

            % boundary values of the problem
            u_new(1,:) = u_exact(1,:); % left vertical
            u_new(:,1) = u_exact(:,1); % bottom
            u_new(end,:) = u_exact(end,:); % right vertical
            u_new(:,end) = u_exact(:,end); % top

            error = 1; % initialize the error
            while 1 % Main Loop
                for k = 2:ny-1
                    for j = 2:nx-1
                        % Gauss-Seidel (G-S) method
                        u_new(j,k) = (u_old(j+1,k) + u_old(j,k+1) + u_new(j-1,k) + u_new(j,k-1))/4;
                        if w_iter > 1
                            % Successive OverRelaxation (SOR) method
                            u_new(j,k) = omega(N_iter) * u_new(j,k) + (1-omega(N_iter)) * u_old(j,k);
                        end
                    end
                end
                if m_iter > 1 % compute the error (8.7.5) in Chapter 8.7
                    c = max(max(abs(u_new-u_old)))/max(max(abs(u_old-u_2old)));
                    error = c/(1-c)*(max(max(abs(u_new-u_old))));
                end
                if error <= epsilon(eps_iter) % error criterion
                    break;
                end
                m_iter = m_iter + 1; % update the error after passing the criterion
                u_2old = u_old; % update from m-1 to m
                u_old = u_new; % update from m to m+1
            end
            if w_iter == 1 % G-S iteration
                iteration(N_iter,eps_iter) = m_iter;
            else % SOR iteration
                iteration_sor(N_iter,eps_iter) = m_iter;
            end
            uval(eps_iter,N_iter,w_iter) = {u_new}; % save the numerical solution
        end
    end
end

% summarize our results in order to obtain the table
N_table = [N(1) N N]';
eps_table = [epsilon(1) repmat(epsilon(2),1,3) repmat(epsilon(3),1,3)]';
iteration = reshape(iteration,[9 1]);
iteration = iteration([1 4:9]);
iteration_sor = reshape(iteration_sor,[9 1]);
iteration_sor = iteration_sor([1 4:9]);

% print Table 8.9
fprintf('\nTable 8.9 Number of iterates necessary to solve (8.8.5)\n')
fprintf('-----\n')
fprintf('   N       epsilon       Gauss-Seidel       SOR       \n')
fprintf('-----\n')
for t = 1:length(N_table)
    fprintf('   %3.0f       %6.4g       %3.0f       %3.0f\n',...
        [N_table(t) eps_table(t) iteration(t) iteration_sor(t)]);
end
fprintf('-----\n')
```

## References.

- [1] Atkinson, K. E. (2008). An introduction to numerical analysis. John wiley & sons.
- [2] Atkinson, K., Han, W., & Stewart, D. E. (2011). Numerical solution of ordinary differential equations (Vol. 108). John Wiley & Sons.
- [3] Atkinson, K. E., & Han, W. (1985). Elementary numerical analysis (p. 17). New York et al.: Wiley.
- [4] Lay, D. C. (2012). Linear algebra and its applications. Addison-Wesley.