

21.1.

Method	General Characteristics
Jacobi	Converges when A is strictly row diagonally dominant.
Gauss-Seidel	Almost always superior to Jacobi because it uses new $x_i$ as soon as they are computed. Converges when A is strictly row diagonally dominant or positive definite.
SOR	With a good choice of $\omega$ , it is superior to Gauss-Seidel and Jacobi. It must be the case that $0 < \omega < 2$ , and SOR converges if A is positive definite.
CG	CG is the method of choice for solving large sparse positive definite systems. If exact arithmetic is used, CG converges in $n$ steps or less. Convergence is related to $\kappa(A)$ . Since $\kappa$ depends on the largest and smallest eigenvalue of A, if the eigenvalues are clustered closely together, convergence will be good. If the eigenvalues of A are widely separated, CG convergence will be slower.
GMRES	Solves general sparse linear systems. If A is positive definite, then GMRES converges for any $m \geq 1$
MINRES	Solves symmetric indefinite sparse linear systems. It is difficult to find a preconditioner for a symmetric indefinite matrix, so if A is ill-conditioned GMRES is likely a better choice.

21.4.

$$\begin{aligned} \text{i)} \quad x^t A y &= (x^t A) y = (Ax)^t y = y^t (Ax) \\ &= x^t (Ay) = (Ay)^t x \end{aligned}$$

$$\begin{aligned} \text{ii)} \quad & \frac{1}{2} (x - \bar{x})^t A (x - \bar{x}) - \frac{1}{2} \bar{x}^t A \bar{x} \\ &= \frac{1}{2} x^t A x - \frac{1}{2} (\bar{x}^t A x + x^t A \bar{x}) \\ &= \frac{1}{2} (x^t A x) - \frac{1}{2} (x^t (A \bar{x}) + x^t (A \bar{x})) = \frac{1}{2} x^t A x - A^t \bar{x} = \phi(x). \end{aligned}$$

$$\text{iii)} \quad \text{If } A > 0, \quad \phi(x) = \frac{1}{2} (x - \bar{x})^t A (x - \bar{x}) - \frac{1}{2} \bar{x}^t A \bar{x} \geq -\frac{1}{2} \bar{x}^t A \bar{x}$$

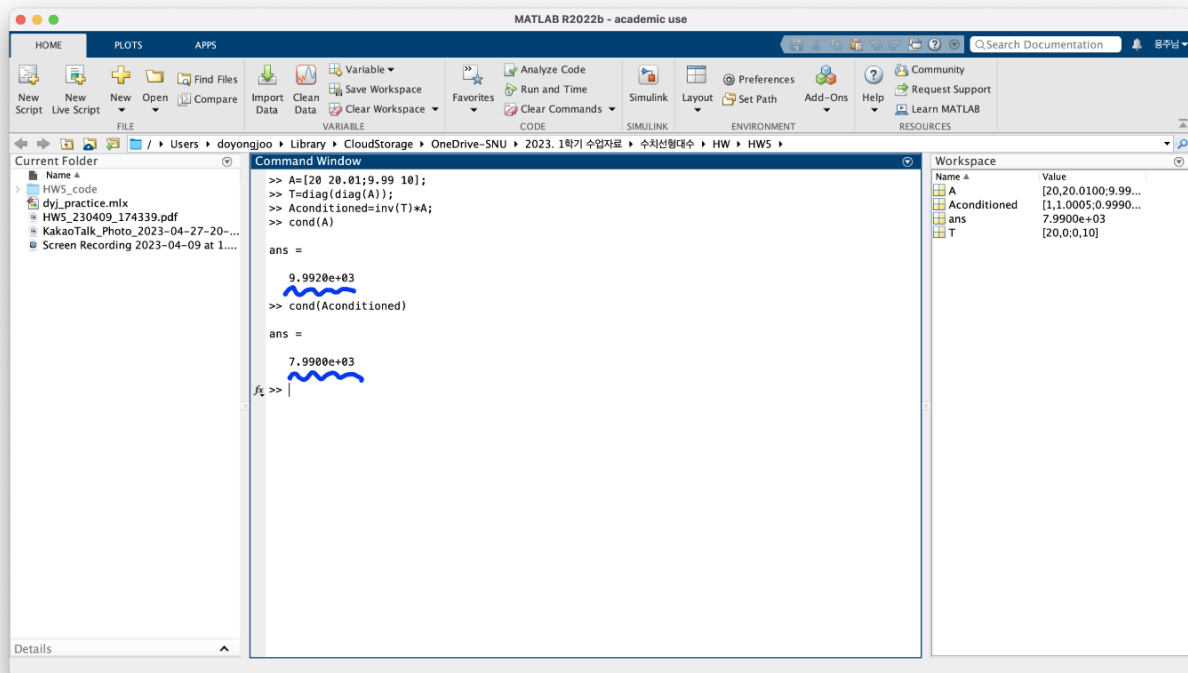
when  $x = \bar{x}$ .



21.1.

i) Divide now  $\sim$  of  $A$  and  $i^{\text{th}}$  element of  $b$  by  $a_{ii}$

ii)



iii) cond. num does not change.



21.10.

$$(D+U)^{-1} \cdot D \cdot (D+L)^{-1} \cdot AX = (D+U)^{-1} \cdot D \cdot (D+L)^{-1} \cdot b$$

$$D \cdot (D+L)^{-1} \cdot AX = D \cdot (D+L)^{-1} \cdot b$$

$$D \cdot (D+L)^{-1} \cdot A (D+U)^{-1} \cdot (D+U) X = D \cdot (D+L)^{-1} \cdot b$$

Let.

$$\begin{cases} \bar{A} = D(D+L)^{-1}A(D+U)^{-1} \\ \bar{b} = D(D+L)^{-1}b \\ \bar{x} = (D+U)X \end{cases}$$

$$\text{For } \underline{(D+L)^{-1} \cdot D \cdot (D+L)^{-1} = I}$$

$$L = (I + LD^{-1}) \sim D(D+L)^{-1} = [I + LD^{-1}]^{-1}$$

$$\begin{aligned}\bar{A} &= (I + LD^{-1})^{-1} \cdot A \cdot (D + U)^{-1} = (I + LD^{-1})^{-1} \cdot (A / (D + U)) \\ &= (I + (L/D))^{-1} \cdot (A / (D + U)) \\ &= (I + (L/D)) \setminus (A / (D + U))\end{aligned}$$

$$\bar{b} = [I + LD^{-1}]^{-1} \cdot b = (I + L/D) \setminus b.$$

$\bar{A}\bar{x} = \bar{b} \rightarrow$  calculate by GMRES, then.

$$x = (D + U) \setminus \bar{x}$$

21.13.

$$\begin{aligned}[u_1 \dots u_m]^t \cdot [w_1, \dots, w_m] \\ = \begin{bmatrix} u_1^t \\ \vdots \\ u_m^t \end{bmatrix} \cdot [w_1, \dots, w_m] = [u_i^t \cdot w_j]_{ij} \\ = [\delta_{ij}]_{ij} = I_m. \quad \square\end{aligned}$$

나머지 정리  $\rightarrow$  전부 다 coding problem

\* 21.23 이 2개나 존재하는데, python 사용해서 mat 파일 /

작동하지 않는 오류가 발생해서 컴파일은 하지 못한 코드입니다.

이제 과제로도 python 코드로 짜서 첨부했습니다.