MATH 231 : Numerical ODEs

Pratham Lalwani

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Question 1: Eigenvalues of special tridiagonal matrices

This question is about finding eigenvalues of tridiagonal linear systems arising from applications, specifically finding the eigenvalues of an $n \times n$ matrix of the form,

$$A = \begin{pmatrix} a & b & & & \\ c & a & b & & \\ & \ddots & \ddots & \ddots & \\ & & c & a & b \\ & & & c & a \end{pmatrix}$$

where a, b, c are real numbers with $bc > 0$ (i.e. b and c have the same signs).

(a) Show that the eigenvalue problem of A is equivalent to the equations

$$cv_{j-1} + (a - \lambda)v_j + bv_{j+1} = 0, \quad j = 1, \dots, n$$
$$v_0 = 0 = v_{n+1}$$

where $\boldsymbol{v} = (v_1, \dots, v_n)^T$ is an eigenvector of A associated with the eigenvalue λ.

(b) The recurrence relation (1) is a second order linear difference equation and can be solved similar to second order linear differential equations. By guessing $v_j = r^j$ for some constant r, show that r satisfies

$$r_\pm = \frac{\lambda - a \pm \sqrt{(\lambda - a)^2 - 4bc}}{2b}, \quad \text{with} \quad r_+ r_- = \frac{c}{b}$$

(c) Show by contradiction that $r_\pm$must be distinct.

Hint: if $r_\pm = r$ are repeated, then $v_j = Ar^j + Bjr^j$ for some constants A, B.

(d) Since $r_\pm$are distinct, the general solution for (1) is $v_j = Ar_+^j + Br_-^j$ for constants A, B. Use this to conclude from (2) and (3) that,

$$\left(\frac{br_+^2}{c}\right)^{n+1} = 1$$

(e) From part (c), (3) and (4), show that $r_\pm$must be complex valued and conclude that (4) has the solutions for $k = 1, \dots, n$,

$$r_{\pm,k} = \sqrt{\frac{c}{b}} \exp\left(\frac{\pm ik\pi}{n+1}\right), \quad \text{where } i = \sqrt{-1}$$

(f) Using part (e), conclude that the eigenvalues of A is given by

$$\lambda_k = a + 2\,\mathrm{sgn}\,(b)\sqrt{bc}\cos\left(\frac{\pi k}{n+1}\right), \quad k = 1, \dots, n$$

(g) Find the eigenvalues of the $n \times n$ finite difference matrix $A_h = \frac{1}{h^2}\begin{pmatrix} 2 & -1 & & & \\ -1 & 2 & \ddots & & \\ & \ddots & \ddots & & \\ & & -1 & 2 & -1 \\ & & & -1 & 2 \end{pmatrix}$, where $h = \frac{1}{n+1}$.

Conclude that A_h is symmetric positive definite and find its condition number $\kappa(A_h)$ with respect to $\|\cdot\|_2$. Show that $\kappa(A_h) = \mathcal{O}(h^{-2})$ as number of grid points n increases. What does this mean for solving $A_h\boldsymbol{x} = \boldsymbol{b}$ when n is large?

Solution

(a) Let $(\lambda, \vec{v})$ be an eigenpair of A

$$
\begin{aligned}
A\vec{v} &= \lambda\vec{v} \\
(A-\lambda I)\,\vec{v} &= \vec{0} \\
\begin{pmatrix} (a-\lambda)\,v_1 + bv_2 \\ cv_1 + (a-\lambda)v_2 + bv_3 \\ \vdots \\ cv_{n-2} + (a-\lambda)v_{n-1} + b_n \\ c_{n-1} + (a-\lambda)v_n \end{pmatrix} &= \vec{0}.
\end{aligned}
$$

We can write the above relation as the following,

$$cv_{j-1} + (a-\lambda)\,v_j + bv_{j+1} = 0. \tag{1}$$

Where $0 \le j \le n+1$ and $v_0 = 0 = v_{n+1}$ 😊

(b) Using the hint we guess the following form of the solution $v_j = r^j$. Substituting in 1,

$$
\begin{aligned}
cr^{j-1} + (a-\lambda)\,r^j + br^{j+1} &= 0 \\
c + (a-\lambda)\,r + br^2 &= 0 \qquad (2) \\
&. \qquad (3)
\end{aligned}
$$

Using the quadratic formula, we get

$$r_{\pm} = \frac{\lambda - a \pm \sqrt{(a-\lambda)^2 - 4bc}}{2b}.$$

As $r_{\pm}$ are the roots to a quadratic, hence

$$r_+ r_- = \frac{c}{b} \tag{4}$$

(c) If 1 has a repeated root, say $r_{\pm} = r$, then solution to the recursion would look like,

$$v_j = Ar^j + Bjr^j.$$

Checking the boundary conditions, $v_0 = 0 = v_{n+1}$

$$v_0 = Ar^0 + B(0)r^0 = A = 0. \tag{5}$$

$$v_{n+1} = (0)r^{n+1} + B(n+1)r^{n+1} = B(n+1)r^{n+1} = 0 \implies B = 0. \tag{6}$$

Combining 5 & 6 gives,

$$v_j = 0.$$

Which is the trivial eigenvector. Hence, we cannot have a repeated root if we want a non-zero eigenvector.

(d) From (c) we have that roots are distinct. Therefore, we look for solutions of the form $v_j = Ar_+^j + Br_-^j$ for some constants A and B defined by the "boundary conditions" of the recursion. We have,

$$
\begin{aligned}
v_0 &= A + B = 0 \implies A = -B \\
v_{n+1} &= Ar_+^{n+1} + Br_-^{n+1} = 0 \implies r_+^{n+1} = r_-^{n+1} \qquad (7)
\end{aligned}
$$

From, 4 and 7, it follows that

$$
\begin{aligned}
\left(r_+^2\right)^{(n+1)} &= \left(\frac{c}{b}\right)^{n+1} \\
\left(\frac{br_+^2}{c}\right)^{(n+1)} &= 1 \qquad (8)
\end{aligned}
$$

(e) We can observe in 8 that $\frac{br_{\pm}^2}{c}$ are the roots of unity, therefore,

$$\frac{br_+^2}{c} = \exp\left(\frac{2k\pi i}{n+1}\right) \implies r_+ = \sqrt{\frac{c}{b}}\exp\left(\frac{k\pi i}{n+1}\right) \quad k = 0, \dots, n.$$

Similarly,

$$\frac{br_-^2}{c} = \exp\left(\frac{2m\pi i}{n+1}\right) \implies r_- = \sqrt{\frac{c}{b}}\exp\left(\frac{m\pi i}{n+1}\right) \quad m = 0, \dots, n.$$

We discard the negative roots because they don't produce any new roots becuase of the relation between r_+ and r_-. Using 4,

$$r_+ r_- = \frac{c}{b}\exp\left(\frac{i(k+m)\pi}{n+1}\right) = \frac{c}{b} \implies k = -m.$$

For $k = 0$ we get,

$$r_+ = r_- = \sqrt{\frac{c}{b}}$$

Which is not possible as repeated roots cannot happen. Therefore we have,

$$r_{\pm,k} = \sqrt{\frac{c}{b}}\exp\left(\frac{\pm ik\pi}{n+1}\right) \quad k = 1, \dots, n.$$

(f) Using the polynomial 2 and relationship between sum quadratic roots and coeffiecients,

$$\begin{aligned} r_+ + r_- &= \frac{\lambda_k - a}{b} \\ \sqrt{\frac{c}{b}}\exp\left(\frac{k\pi i}{n+1}\right) + \sqrt{\frac{c}{b}}\exp\left(\frac{-k\pi i}{n+1}\right) &= \frac{\lambda_k - a}{b} \\ \operatorname{sgn}(b)\sqrt{bc}\exp\left(\frac{k\pi i}{n+1}\right) + \operatorname{sgn}(b)\sqrt{bc}\exp\left(\frac{-k\pi i}{n+1}\right) &= \lambda_k - a \\ a + \operatorname{sgn}(b)\sqrt{bc}\left(\exp\left(\frac{k\pi i}{n+1}\right) + \exp\left(\frac{-k\pi i}{n+1}\right)\right) &= \lambda_k \\ a + 2\operatorname{sgn}(b)\sqrt{bc}\cos\left(\frac{k\pi}{n+1}\right) &= \lambda_k \\ . \end{aligned}$$

Which is the desired result.

(g) For the given matrix A_h, we have,

$$a = 2, \quad b = c = -1.$$

Using the formula derived above,

$$\lambda_k = 2 - 2\cos\left(\frac{k\pi}{n+1}\right) \qquad k = 1, \dots, n.$$

As $k = 1, \dots, n \implies -1 < \cos\left(\frac{k\pi}{n+1}\right) < 1 \implies \lambda_k > 0 \quad k = 1, \dots, n \implies A$ is SPD.

We get, λ_{max} when $k = 1$ and λ_{min} when $k = n$. As A is SPD, therefore, $\kappa(A_h)$ in ℓ_2 norm is defined as follows,

$$\begin{aligned}
\kappa(A_h) &= \frac{\lambda_{max}}{\lambda_{min}} \\
&= \frac{2 - 2\cos\left(\frac{n\pi}{n+1}\right)}{2 - 2\cos\left(\frac{\pi}{n+1}\right)} \\
&= \frac{2 - 2(1 - \frac{1}{2}\left(\frac{n\pi}{n+1}\right)^2 + \mathcal{O}\left(h^4\right))}{2 - 2(1 - \frac{1}{2}\left(\frac{\pi}{n+1}\right)^2 + \mathcal{O}\left(h^4\right))} \\
&= \frac{\left(\frac{n\pi}{n+1}\right)^2 + \mathcal{O}\left(h^4\right)}{\left(\frac{\pi}{n+1}\right)^2 + \mathcal{O}\left(h^4\right)} \\
&= \frac{n^2 + \mathcal{O}\left(h^2\right)}{1 + \mathcal{O}\left(h^2\right)} \\
&= \mathcal{O}(n^2) = \mathcal{O}\left(h^{-2}\right)
\end{aligned}$$

Therefore, as $\kappa(A_h)$ increases by 10 times, we lose 2 digits of accuracy atleast for direct methods.

Question 2: Classical iterative methods for strictly diagonally dominant matrices

(a) Show that the diagonal part of any strictly diagonally dominant (S.D.D.) matrix is invertible.

(b) Recall the Gershgorin's theorem below, which can give useful information about the eigenvalues of a matrix. The eigenvalues of a complex valued matrix A lies in the union of n discs $\bigcup_{i=1}^{n} D_i$ on the complex plane, where

$$D_i = \left\{ z \in \mathbb{C} : |z - a_{ii}| \leqslant \sum_{j \neq i} \left|a_{ij}\right| \right\}$$

Using Gershgorin's theorem, conclude S.D.D. matrices are invertible. Hint: Show that $0 \notin D_i$ for all $i = 1, \ldots, n$.

The next two parts are about showing convergence of Jacobi and Gauss-Seidel iterations for S.D.D. matrices.

(c) Recall the matrix $-M^{-1}N$ associated with the Jacobi iteration takes the form $-D^{-1}(L + U)$, where $A = L + D + U$.

(i) Let A be S.D.D. and λ be any eigenvalue of $-D^{-1}(L+U)$. Show that $\det(L+U+\lambda D) = 0$ using part (a).

(ii) Now suppose $|\lambda| \geqslant 1$. Deduce from A being S.D.D. that $L + U + \lambda D$ must also be S.D.D.

(iii) Deduce a contradiction by applying the result from part (b) to $L + U + \lambda D$, and conclude that $|\lambda| < 1$.

(iv) Combine parts (i)-(iii) to conclude that Jacobi iteration converges for S.D.D. matrices.

(d) Follow a similar argument as part (c) to show that Gauss-Seidel iterations converges for S.D.D. matrices.

Solution

(a) Let A be a S.D.D matrix and,

$$\implies a_{ii} > \sum_{\substack{j=1 \\ j\neq i}}^{n} a_{ij} \geq 0 \implies a_{ii} > 0 \quad \forall 1 \leq i \leq n.$$

Let D be the matrix containing the diagonial entries of A, hence

$$D = \begin{bmatrix} a_{11} & & \\ & \ddots & \\ & & a_{nn} \end{bmatrix}.$$

As, all $a_{ii} > 0$, therefore we D^{-1} exists.

(b) Let λ_i be the eigenvalues associated with disc D_i.
Suppose $0 \in D_i$ for some $1 \leq i \leq n$, therefore, we have,

$$a_{ii} \leqslant \sum_{\substack{j=0 \\ j\neq i}}^{n} a_{ij}.$$

Which is false as A is a S.D.D matrix, hence , $0 \notin D_i$.
Therefore we have, $|\lambda_i| > 0 \quad \forall i, 1 \leq i \leq n \implies A^{-1}$ exists.

(c) (i) Given that λ is an eigenvalue of $-D^{-1}(L+U)$. Therefore we have $\vec{v}$ such that $\vec{v} \neq 0$,

$$\begin{aligned} -D^{-1}(L+U)\vec{v} &= \lambda\vec{v} \\ (L+U)\vec{v} &= -\lambda D\vec{v} \\ (L+U+\lambda D)\vec{v} &= \vec{0}. \end{aligned}$$

As there is a non-zero null vector associated with $L+U+\lambda D$, therefore $\det(L+U+\lambda D) = 0$.

(ii) Given that A is S.D.D. Suppose $|\lambda| \geq 1$. Consider,

$$\begin{aligned} |(L+U+\lambda D)_{ii}| = |\lambda a_{ii}| &= |\lambda||a_{ii}| \\ &> |\lambda|| \sum_{\substack{j=1 \\ j\neq i}}^{n} a_{ij}| \\ &\geq |\sum_{\substack{j=1 \\ j\neq i}}^{n} a_{ij}| \\ &= |\sum_{\substack{j=1 \\ j\neq i}}^{n} (L+U+\lambda D)_{ij}| \end{aligned}$$

Hence, $(L+U+\lambda D)$ is S.D.D. .

(iii) If $|\lambda| \geq 1$ and A is S.D.D, gives that $(L+U+\lambda D)$ is S.D.D .
Therefore, $(L+U+\lambda D)$ is invertible. Which is a contradiction as $det(L+U+\lambda D) = 0$. Therefore, $|\lambda| < 1$.

(iv) Let $M = D$ and $N = L + U$. From parts (i)-(iii) we get,

$$\lambda_i \leqslant \lambda_{max} < 1 \implies \rho(-M^{-1}N) < 1.$$

By theorem of convergence of iterative solvers we get, iterations based on $-M^{-1}N$ converges to 0.

(d) **Note:-**
$L + D$ is invertible as the diagonal part is invertible and this would mean that $\det(L + D) \neq 0$.

(i) Let λ be an eigenvalue of $-(L + D)^{-1}(U)$. Therefore we have $\vec{v}$ such that $\vec{v} \neq 0$,

$$\begin{aligned} -(L + D)^{-1}(L + U)\vec{v} &= \lambda\vec{v} \\ (U)\vec{v} &= -\lambda(L + D)\vec{v} \\ (U + \lambda(L + D))\vec{v} &= \vec{0}. \end{aligned}$$

As there is a non-zero null vector associated with $U + \lambda(L + D)$, therefore $\det(U + \lambda(L + D)) = 0$.

(ii) Given that A is S.D.D. Suppose $|\lambda| \geq 1$. Consider,

$$\begin{aligned} |(U + \lambda(L + D))_{ii}| = |\lambda a_{ii}| &= |\lambda||a_{ii}| \\ &> |\lambda|| \sum_{\substack{j=1 \\ j\neq i}}^{n} a_{ij}| \\ &\geq |\lambda \sum_{j=1}^{i-1} a_{ij} + \sum_{j=i+1}^{n} a_{ij}| \\ &= |\sum_{\substack{j=1 \\ j\neq i}}^{n} (U + \lambda(L + D))_{ij}| \end{aligned}$$

Hence, $(U + \lambda(L + D))$ is S.D.D. .

(iii) If $|\lambda| \geq 1$ and A is S.D.D, gives that $(U + \lambda(L + D))$ is S.D.D .
Therefore, $(L + U + \lambda(L + D))$ is invertible. Which is a contradiction as $det(U + \lambda(L + D)) = 0$.
Therefore, $|\lambda| < 1$.

(iv) Let $M = L + D$ and $N = U$. From parts (i)-(iii) we get,

$$\lambda_i \leqslant \lambda_{max} < 1 \implies \rho(-M^{-1}N) < 1.$$

By theorem of convergence of iterative solvers we get, iterations based on $-M^{-1}N$ converges to 0.

Question 3: Classical iterative methods for symmetric positive definite matrices

This question is about coding and comparing classical iterative methods for the S.P.D. matrix A_h from Q1(g).

(a) Write a pseudocode for the classical iterative methods: Richardson, optimal Richardson, Jacobi, Gauss-Seidel, S.O.R., and optimal S.O.R.

(b) Implement a program to solve $A_h\boldsymbol{x} = \boldsymbol{b}$ with $\boldsymbol{b} = (1, \ldots, 1)^T \in \mathbb{R}^{20}$ and $\boldsymbol{x}_0 = (1, 0, \ldots, 0)^T \in \mathbb{R}^{20}$ using Richardson (with $\omega = \lambda_{\max}^{-1}$), optimal Richardson, Jacobi, Gauss-Seidel, S.O.R. (with $\theta = 1.2$

) and optimal S.O.R. Generate a plot comparing the log of their residual in ℓ_2 norm versus iterations up to 5000 . Rank the performance of each method by comparing the iterations needed to reach the residual tolerance of 10^{-14}. Use sparse representation when appropriate.
Hint: Use Q1(g) to find parameters for Richardson and vary θ to find an approximate optimal parameter for S.O.R.

(c) Comment on the decreases in performance when $n = 1000$. Explain briefly how this relates to $\kappa(A_h) = \mathcal{O}(h^{-2})$.

Solution

Algorithm 1: Richardson Iteration

function RichardsonIteration(A,b,$\boldsymbol{x}_0$,ω,tol,$maxIter$):
  Input:
  A: The matrix to find the solution to
  $\boldsymbol{b}$: The resultant vector in $A\boldsymbol{x} = \boldsymbol{b}$
  $\boldsymbol{x}_0$: The initial guess
  ω: Richardson parameter (fixed)
  maxIter: The maximum of iterations
  Output: x: The solution to $A\boldsymbol{x} = \boldsymbol{b}$

  $M \leftarrow \omega^{-1} I$
  $N \leftarrow A - M$
  $x \leftarrow x_0$
  $\boldsymbol{r} \leftarrow \boldsymbol{b} - A\boldsymbol{x}$
  while $\|r\|_2 < tol$ **and** $i < maxIter$:
    $\boldsymbol{x} \leftarrow \boldsymbol{x} + \omega \boldsymbol{r}$
    $\boldsymbol{r} \leftarrow \boldsymbol{b} - A\boldsymbol{x}$
  end
  return $\boldsymbol{x}$

Algorithm 2: Optimal Richardson Iteration

function OptimalRichardsonIteration(A,$\boldsymbol{b}$,$\boldsymbol{x}_0$,tol,$maxIter$):
  Input:
  A: The matrix to find the solution to
  $\boldsymbol{b}$: The resultant vector in $A\boldsymbol{x} = \boldsymbol{b}$
  $\boldsymbol{x}_0$: The initial guess
  maxIter: The maximum of iterations
  Output: x: The solution to $A\boldsymbol{x} = \boldsymbol{b}$

  $\omega \leftarrow \dfrac{2}{\lambda_{max}(A) + \lambda_{min}(A)}$
  $M \leftarrow \omega^{-1} I$
  $N \leftarrow A - M$
  $x \leftarrow x_0$
  $\boldsymbol{r} = \boldsymbol{b} - A\boldsymbol{x}$
  while $\|r\|_2 < tol$ **and** $i < maxIter$:
    $\boldsymbol{x} \leftarrow \boldsymbol{x} + \omega \boldsymbol{r}$
    $\boldsymbol{r} \leftarrow \boldsymbol{b} - A\boldsymbol{x}$
  end
  return $\boldsymbol{x}$

Algorithm 3: Jacobi Iteration

```
function JacobiIteration(A,b,x_0,tol,maxIter ):
    Input:
    A:The matrix to find the solution to
    b: The resultant vector in Ax = b
    x_0: The initial guess
    maxIter: The maximum of iterations
    Output: x: The solution to Ax = b

    M ←diag(A)
    N ← A − M
    x ← x_0
    r ← b − Ax
    while ||r||_2 < tol and i < maxIter:
        x ← M^{-1}(x + b − Nx)
        r ← b − Ax
        i = i + 1
    end
    return x
```

Algorithm 4: Gauss-Seidel Iteration

```
function GaussSeidelIteration(A,b,x_0,tol,maxIter ):
    Input:
    A: The matrix to find the solution to
    b: The resultant vector in Ax = b
    x_0: The initial guess
    maxIter: The maximum of iterations
    Output: x: The solution to Ax = b

    M ←diag(A)+lower(A)
    N ← A − M
    x ← x_0
    r ← b − Ax
    i ← 0
    while ||r||_2 < tol and i < maxIter:
        x ← M^{-1}(x + b − Nx)
        r ← b − Ax
        i = i + 1
    end
    return x
```

Algorithm 5: SOR Iteration

function SORIteration(A, $\boldsymbol{b}$, $\boldsymbol{x}_0$, θ, tol, $maxIter$):

Input:
A: The matrix to find the solution to
$\boldsymbol{b}$: The resultant vector in $A\boldsymbol{x} = \boldsymbol{b}$
$\boldsymbol{x}_0$: The initial guess
θ: Amplification Parameter
maxIter: The maximum of iterations
Output: x: The solution to $A\boldsymbol{x} = \boldsymbol{b}$

$M \leftarrow \mathrm{diag}(A) + \mathrm{lower}(A)$
$N \leftarrow A - M$
$\boldsymbol{x} \leftarrow \boldsymbol{x}_0$
$\boldsymbol{r} \leftarrow \boldsymbol{b} - A\boldsymbol{x}$
$i \leftarrow 0$
while $\|r\|_2 < tol$ ***and*** $i < maxIter$**:**
    $\boldsymbol{x} \leftarrow (1-\theta)x + \theta M^{-1}(\boldsymbol{x} + \boldsymbol{b} - N\boldsymbol{x})$
    $\boldsymbol{r} \leftarrow \boldsymbol{b} - A\boldsymbol{x}$
    $i = i + 1$
end
return $\boldsymbol{x}$

Question 4: Steepest Descent and Conjugate Gradient

(a) Let A be a S.P.D. matrix. Show that $(\boldsymbol{x}, \boldsymbol{y})_A := \boldsymbol{x}^T A \boldsymbol{y}$ for $\boldsymbol{x}, \boldsymbol{y} \in \mathbb{R}^n$ forms an inner product on $\mathbb{R}^n$.

(b) Using part (a), conclude that $\|\boldsymbol{x}\| = (\boldsymbol{x}, \boldsymbol{x})_A^{1/2}$ for $\boldsymbol{x} \in \mathbb{R}^n$ is a norm on $\mathbb{R}^n$.

Hint: You can assume the Cauchy-Schwarz inequality $|(\boldsymbol{x}, \boldsymbol{y})_A| \leqslant \|\boldsymbol{x}\|_A \|\boldsymbol{y}\|_A$ holds.

(c) For the method of Steepest Descent, show that $\nabla f(\boldsymbol{x}_k)$ and $\nabla f(\boldsymbol{x}_{k+1})$ are orthogonal (i.e. zig-zaging behavior), where $f(\boldsymbol{y}) = \frac{1}{2}\boldsymbol{y}^T A \boldsymbol{y} - \boldsymbol{y}^T \boldsymbol{b}$. Hint: Recall how the step size for Steepest Descent is determined.

(d) Repeat the experiment from **Q3(b)** with $\boldsymbol{b} = (1, \ldots, 1)^T \in \mathbb{R}^{1000}$ and $\boldsymbol{x}_0 = (1, 0, \ldots, 0)^T \in \mathbb{R}^{1000}$ using the method of Steepest Descent and Conjugate Gradient. Generate a plot comparing the log of their residual in ℓ_2 norm versus iterations up to 5000 . Rank their performance by comparing the iterations needed to reach the residual tolerance of 10^{-14}, as well as versus the classical iterative methods. Verify your CG method terminates after the desired number of iterations. Use sparse representation when appropriate.

Solution

(a) $(.,.)$ is an inner-product if :

(i) Conjugate Symmetery:

$$(x, y)_A = (y, x)_A.$$

(ii) Linearity

$$(a\vec{x} + b\vec{y}, \vec{z})_A = a\,(\vec{x}, \vec{z})_A + b\,(\vec{y}, \vec{z})_A\,.$$

(iii) Positive-Definiteness:

$$\left(\vec{x},\vec{x}\right)_A > 0.$$

(i)
$$\left(x,y\right)_A = x^T A y = y^T A x = \left(y,x\right)_A.$$

(ii)
$$\left(a\vec{x}+b\vec{y},\vec{z}\right)_A = (a\vec{x}+b\vec{y})^T A\vec{z} = a\vec{x}^T A\vec{z} + b\vec{y}^T A\vec{z} = a\left(\vec{x},\vec{z}\right)_A + b\left(\vec{y},\vec{z}\right)_A.$$

(iii)
$$(x,x)_A = \vec{x}^T A\vec{x} > 0 \quad \text{As } A \text{ as is SPD.}$$

Therefore, $(.,.)_A$ is an inner-product.

(b) $\|.\|_A$ is an norm if :

(i) Positive Definitness :

$$\|x\|_A > 0 \quad \forall\vec{x} \neq 0 \quad \wedge \quad \|\vec{x}\|_A = 0 \iff \vec{x} = \vec{0}.$$

(ii) Scalar Multiplication

$$\|\lambda\vec{x}\|_A = \lambda\|\vec{x}\|_A.$$

(iii) Sub-additivity (Triangle Inequality):

$$\|\vec{x}+\vec{y}\|_A = \|\vec{x}\|_A + \|\vec{y}\|_A.$$

(i) Let $x \in \mathbb{R}^n$ and $\vec{x} \neq \vec{0}$
$$\|x\|_A = \sqrt{\vec{x}^T A\vec{x}} > 0 \quad \text{,as } A \text{ is SPD.}$$

Let $\|\vec{x}\|_A = 0$
$$\|\vec{x}\|_A = 0 = \sqrt{\vec{x}^T A\vec{x}} \iff \vec{x} = 0 \quad \text{, as } A \text{ is SPD.}$$

(ii) Scalar Multiplication

$$\|\lambda\vec{x}\|_A = \sqrt{\lambda\vec{x}^T A\lambda\vec{x}} = \sqrt{\lambda^2\vec{x}^T A\vec{x}} = \lambda\|\vec{x}\|_A.$$

(iii) Sub-additivity (Triangle Inequality):

$$\begin{aligned}
\|\vec{x}+\vec{y}\|_A &= \sqrt{\left(\vec{x}+\vec{y}\right)^T A\left(\vec{x}+\vec{y}\right)} \\
&= \sqrt{\vec{x}^T A\vec{x} + \vec{x}^T A\vec{y} + \vec{y}^T A\vec{x} + \vec{y}^T A\vec{y}} \\
&= \sqrt{\vec{x}^T A\vec{x} + 2\vec{x}^T A\vec{y} + \vec{y}^T A\vec{y}} \\
&= \sqrt{\|\vec{x}\|_A^2 + 2\left(\vec{x},\vec{y}\right) + \|\vec{y}\|_A^2} \\
&\leq \sqrt{\|\vec{x}\|_A^2 + 2\|\vec{x}\|_A\|\vec{y}\|_A + \|\vec{y}\|_A^2} \\
&= \|\vec{x}\|_A + \|\vec{y}\|_A.
\end{aligned}$$

Therefore, $\|x\|_A$ is valid norm.

(c) For a step k we have to minimize f along step length λ,

$$g(\lambda) = f(\vec{x}_k + \lambda\vec{r}_k).$$

Taking the derivative on both sides and setting it to 0 (because minimization),

$$\begin{aligned} 0 = g'(\lambda) &= \nabla f(\vec{x}_k + \lambda\vec{r}_k)^T r_k \\ &= \nabla f(x_{k+1})^T r_k \end{aligned}$$
.

From class we also know that $\nabla f(\vec{x}) = A\vec{x} - \vec{b} = r$, therefore,

$$\begin{aligned} 0 = g'(\lambda) &= \nabla f(x_{k+1})^T r_k \\ &= \nabla f(\vec{x}_{k+1})^T \nabla f(\vec{x}_k) = 0 \end{aligned}$$
.

Which means $\nabla f(\vec{x}_{k+1})$ and $\nabla f(\vec{x}_k)$ are orthogonal.