NATIONAL UNIVERSITY OF SINGAPORE

Department of Mathematics

MA1101R Linear Algebra I

2018-2019 (Semester 1)

Tutorial 10

- 1. Let \boldsymbol{A} be a symmetric matrix. If \boldsymbol{u} and \boldsymbol{v} are two eigenvectors of \boldsymbol{A} associated with eigenvalues λ and μ , respectively, where $\lambda \neq \mu$, show that $\boldsymbol{u} \cdot \boldsymbol{v} = 0$ by following the following steps.
 - (a) Show that $\mathbf{v}^T \mathbf{A} = \mu \mathbf{v}^T$.

Since \boldsymbol{v} is an eigenvector of \boldsymbol{A} associated with eigenvalue μ , we have $\boldsymbol{A}\boldsymbol{v} = \mu \boldsymbol{v}$. By $\boldsymbol{A} = \boldsymbol{A}^T$, $\boldsymbol{v}^T \boldsymbol{A} = \boldsymbol{v}^T \boldsymbol{A}^T = (\boldsymbol{A}\boldsymbol{v})^T = \mu \boldsymbol{v}^T$.

(b) Show that $\mathbf{v}^T \mathbf{A} \mathbf{u} = \mu \mathbf{v} \cdot \mathbf{u}$.

By Part (a), $\mathbf{v}^T \mathbf{A} \mathbf{u} = (\mathbf{v}^T \mathbf{A}) \mathbf{u} = \mu \mathbf{v} \cdot \mathbf{u}$.

(c) Show that $\mathbf{v}^T \mathbf{A} \mathbf{u} = \lambda \mathbf{v} \cdot \mathbf{u}$.

Since u is an eigenvector of A associated with eigenvalue λ , we have $Au = \lambda u$. Then $v^T Au = v^T (Au) = \lambda v \cdot u$.

(d) Show that $\boldsymbol{u} \cdot \boldsymbol{v} = 0$.

By Parts (b) and (c), $\lambda \boldsymbol{v} \cdot \boldsymbol{u} = \mu \boldsymbol{v} \cdot \boldsymbol{u}$. As $\mu \neq \lambda$, we have $\boldsymbol{v} \cdot \boldsymbol{u} = 0$.

2. Let

$$\mathbf{A} = \begin{pmatrix} b & a & a \\ a & b & a \\ a & a & b \end{pmatrix}.$$

(a) Show that **A** has eigenvalues b - a and 2a + b.

Since

$$\det(\lambda \mathbf{I} - \mathbf{A}) = \lambda^3 - 3b\lambda^2 - 3a^2\lambda + 3b^2\lambda - 2a^3 + 3a^2b - b^3$$

= $(\lambda - (b - a))^2(\lambda - (2a + b)),$

the eigenvalues are b-a and 2a+b.

(b) Find an orthogonal basis of the eigenspace E_{b-a} .

For $\lambda = b - a$, the linear system $(\lambda \mathbf{I} - \mathbf{A})\mathbf{x} = \mathbf{0}$ is

Solving the linear system, by the assumption $a \neq 0$, we have

$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} = t \begin{pmatrix} -1 \\ 0 \\ 1 \end{pmatrix} + s \begin{pmatrix} -1 \\ 1 \\ 0 \end{pmatrix}$$

where t and s are arbitrary parameters. So $\{(-1,1,0)^T, (-1,0,1)^T\}$ is a basis for E_{b-a} . By Gram-Schmidt Process, we obtain an orthonormal basis

$$\{(-\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}}, 0)^T, (-\frac{1}{\sqrt{6}}, -\frac{1}{\sqrt{6}}, \frac{2}{\sqrt{6}})^T\}$$

for E_{b-a} .

If a = 0, we may choose the standard basis.

(c) Find an orthogonal basis of the eigenspace E_{2a+b} .

For $\lambda = 2a + b$, the linear system $(\lambda \mathbf{I} - \mathbf{A})\mathbf{x} = \mathbf{0}$ is

$$\begin{pmatrix} 2a & -a & -a \\ -a & 2a & -a \\ -a & -a & 2a \end{pmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

Solving the linear system, by the assumption $a \neq 0$, we have

$$\begin{pmatrix} x \\ y \\ z \end{pmatrix} = t \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$$

where t is arbitrary parameters. So $\{(1,1,1)^T\}$ is a basis for E_{2a+b} . By Gram-Schmidt Process, we obtain an orthonormal basis $\{(\frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}}, \frac{1}{\sqrt{3}})^T\}$ for E_{2a+b} . If a=0, we may choose the standard basis.

(d) Find a matrix P that orthogonally diagonalize A. and determine P^TAP .

Form the matrix \boldsymbol{P} by using the orthonormal bases as the column vectors:

$$\mathbf{P} = \begin{pmatrix} -\frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{6}} & \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{6}} & \frac{1}{\sqrt{3}} \\ 0 & \frac{2}{\sqrt{6}} & \frac{1}{\sqrt{3}} \end{pmatrix} \text{ and } \mathbf{P}^T \mathbf{A} \mathbf{P} = \begin{pmatrix} b - a & 0 & 0 \\ 0 & b - a & 0 \\ 0 & 0 & 2a + b \end{pmatrix} = \begin{pmatrix} b & a & a \\ a & b & a \\ a & a & b \end{pmatrix}.$$

3. Let

$$\mathbf{A} = \begin{pmatrix} 2 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 2 \end{pmatrix}.$$

(a) Compute A^4 .

Following Question (2), we have

$$\boldsymbol{P}^T \boldsymbol{A} \boldsymbol{P} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 4 \end{pmatrix},$$

where

$$\boldsymbol{P} = \begin{pmatrix} -\frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{6}} & \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{6}} & \frac{1}{\sqrt{3}} \\ 0 & \frac{2}{\sqrt{6}} & \frac{1}{\sqrt{3}} \end{pmatrix}$$

is obtained in Question (2). By $\mathbf{P}^T = \mathbf{P}^{-1}$,

$$\mathbf{A}^4 = \mathbf{P} \begin{pmatrix} 1^4 & 0 & 0 \\ 0 & 1^4 & 0 \\ 0 & 0 & 4^4 \end{pmatrix} \mathbf{P}^T = \begin{pmatrix} 86 & 85 & 85 \\ 85 & 86 & 85 \\ 85 & 85 & 86 \end{pmatrix}.$$

Remark: To obtain A^4 , we can compute the matrices multiplication. Or by Question (2), note that

$$\mathbf{P} \begin{pmatrix} b-a & 0 & 0 \\ 0 & b-a & 0 \\ 0 & 0 & 2a+b \end{pmatrix} \mathbf{P}^T = \begin{pmatrix} b & a & a \\ a & b & a \\ a & a & b \end{pmatrix}.$$

Applying this matrix equation to our case, let

$$\begin{pmatrix} b-a & 0 & 0 \\ 0 & b-a & 0 \\ 0 & 0 & 2a+b \end{pmatrix} = \begin{pmatrix} 1^4 & 0 & 0 \\ 0 & 1^4 & 0 \\ 0 & 0 & 4^4 \end{pmatrix}.$$

We establish a linear system

$$\begin{cases} b - a = 1 \\ 2a + b = 256 \end{cases}$$

Solve for a = 85 and b = 86 and then obtain the same result.

Note that the second method heavily relies on the symmetry of the matrix A, which is a shortcut to compute A^4 . However, it is not always the case.

(b) Find a matrix \boldsymbol{B} such that $\boldsymbol{B}^2 = \boldsymbol{A}$.

Similar to Part (a), since

$$\begin{pmatrix} \pm 1 & 0 & 0 \\ 0 & \pm 1 & 0 \\ 0 & 0 & \pm 2 \end{pmatrix}^2 = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 4 \end{pmatrix}$$

we may take

$$\boldsymbol{B} = \boldsymbol{P} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{pmatrix} \boldsymbol{P}^T = \begin{pmatrix} \frac{4}{3} & \frac{1}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{4}{3} & \frac{1}{3} \\ \frac{1}{3} & \frac{1}{3} & \frac{4}{3} \end{pmatrix}.$$

4. A square matrix $(a_{ij})_{n\times n}$ is called a stochastic matrix if all the entries are non-negative and the sum of entries of each column is 1, i.e. $a_{1i} + a_{2i} + \cdots + a_{ni} = 1$ for $i = 1, 2, \ldots, n$.

Let \boldsymbol{A} be a stochastic matrix.

(a) Show that $(1, 1, ..., 1)^T$ is an eigenvector of \mathbf{A}^T .

Let \boldsymbol{u} be the row matrix $(1, 1, \dots, 1)$. Then

$$uA = (\sum_{i=1}^{n} a_{i1}, \sum_{i=1}^{n} a_{i2}, \dots, \sum_{i=1}^{n} a_{in}) = u,$$

that is, $\mathbf{A}^T \mathbf{u}^T = \mathbf{u}^T$. Then $(1, 1, \dots, 1)^T$ is an eigenvector of \mathbf{A}^T .

(b) Show that 1 is an eigenvalue of \boldsymbol{A} .

Since $\mathbf{A}^T \mathbf{u}^T = \mathbf{u}^T$, 1 is an eigenvector of \mathbf{A}^T . Since \mathbf{A} and \mathbf{A}^T have the same characteristic polynomials (see Homework 4), 1 is an eigenvalue of \mathbf{A} .

(c) Show that \mathbf{A}^k for $k \geq 0$ is a stochastic matrix.

Let u be the row matrix (1, 1, ..., 1). By definition, for a square matrix B, B is a stochastic matrix if and only if uB = u. By uA = u, we have

$$uA^k = uA^{k-1} = \cdots = u$$
.

For k = 0, $\mathbf{A} = I_n$, which is a stochastic matrix. Therefore, for all $k \geq 0$, \mathbf{A}^k is a stochastic matrix.

(d) Let $\mathbf{u} = (u_1, u_2, \dots, u_n)^T$ be an eigenvector of \mathbf{A}^T associated an eigenvalue λ and denote

$$u_{\text{max}} = \max\{u_1, u_2, \dots, u_n\} \text{ and } u_{\text{min}} = \min\{u_1, u_2, \dots, u_n\},\$$

that is, u_{max} and u_{min} are the maximum and minimum elements in the set $\{u_1, u_2, \ldots, u_n\}$, respectively.

Show that $\lambda u_j \leq u_{\text{max}}$ and $u_{\text{min}} \leq \lambda u_j$ for all $1 \leq j \leq n$.

Since $\mathbf{u} = (u_1, u_2, \dots, u_n)^T$ be an eigenvector of \mathbf{A}^T associated to eigenvalue λ , we have

$$\mathbf{A}^{T}\mathbf{u} = (\sum_{i=1}^{n} a_{i1}u_{i}, \sum_{i=1}^{n} a_{i2}u_{i}, \dots, \sum_{i=1}^{n} a_{in}u_{i})^{T} = \lambda(u_{1}, u_{2}, \dots, u_{n})^{T}.$$
 (1)

Since all a_{ij} are nonnegative,

$$u_{\min} = (\sum_{i=1}^{n} a_{ij})u_{\min} \le \sum_{i=1}^{n} a_{ij}u_{i} \le (\sum_{i=1}^{n} a_{ij})u_{\max} = u_{\max}.$$

By Equation (1), $\sum_{i=1}^{n} a_{ij}u_i = \lambda u_j$. Thus for all $1 \leq j \leq n$, $u_{\min} \leq \lambda u_j \leq u_{\max}$.

(e) If λ is an eigenvalue of \boldsymbol{A} , then $\lambda \leq 1$.

Since A and A^T have the same characteristic function and λ is an eigenvalue of A, λ is also an eigenvalue of A^T .

By Part (d), $\lambda u_{\text{max}} \leq u_{\text{max}}$ and $u_{\text{min}} \leq \lambda u_{\text{min}}$. If $u_{\text{max}} \geq 0$, then $\lambda \leq 1$ by $\lambda u_{\text{max}} \leq u_{\text{max}}$; If $u_{\text{max}} < 0$, then $u_{\text{min}} \leq u_{\text{max}} < 0$ and $\lambda \leq 1$ by $u_{\text{min}} \leq \lambda u_{\text{min}}$. In all cases, we have $\lambda \leq 1$.

(f) If λ is an eigenvalue of \boldsymbol{A} , then $|\lambda| \leq 1$. (Hint: Apply Question (4e) to \boldsymbol{A}^2 .)

Since λ^2 is an eigenvalue of \mathbf{A}^2 and \mathbf{A}^2 is a stochastic matrix (see Part (c)), we have $\lambda^2 \leq 1$ as above by Part (e). Hence $|\lambda| \leq 1$.

5. (This is an induction step for proving Remark 6.2.5.3.) Let \boldsymbol{A} be a square matrix of order n. By Theorem 6.2.3, to diagonalize \boldsymbol{A} , we need to find n linearly independent eigenvectors.

Suppose we already have m(< n) linearly independent eigenvectors $\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_m$, say, $\mathbf{A}\mathbf{u}_i = \lambda_i \mathbf{u}_i$ for $i = 1, 2, \dots, m$ where $\lambda_1, \lambda_2, \dots, \lambda_m$ are not necessarily distinct. For a new eigenvalue μ ($\mu \neq \lambda_i$ for $i = 1, 2, \dots, m$) of \mathbf{A} , let $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_p\}$ be a basis for the eigenspace E_{μ} . Prove that $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_m, \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_p\}$ is linearly independent.

(Hint: Consider the vector equation

$$a_1\boldsymbol{u}_1 + a_2\boldsymbol{u}_2 + \dots + a_m\boldsymbol{u}_m + b_1\boldsymbol{v}_1 + b_2\boldsymbol{v}_2 + \dots + b_p\boldsymbol{v}_p = \boldsymbol{0}.$$

By using the property of eigenvectors, show that

$$a_1(\lambda_1 - \mu)\boldsymbol{u}_1 + a_2(\lambda_2 - \mu)\boldsymbol{u}_2 + \dots + a_m(\lambda_m - \mu)\boldsymbol{u}_m = \mathbf{0}.$$

Then make use of the linearly independent assumption on u_1, u_2, \ldots, u_m , as well as v_1, v_2, \ldots, v_p , to finish the proof.)

Let a_i and b_j for $1 \le i \le m$ and $1 \le j \le p$ be the constant such that

$$a_1 \mathbf{u}_1 + a_2 \mathbf{u}_2 + \dots + a_m \mathbf{u}_m + b_1 \mathbf{v}_1 + b_2 \mathbf{v}_2 + \dots + b_p \mathbf{v}_p = \mathbf{0}.$$
 (2)

Taking the pre-multiplication of \mathbf{A} to the both sides of (2), we have

$$a_1 \mathbf{A} \mathbf{u}_1 + a_2 \mathbf{A} \mathbf{u}_2 + \dots + a_m \mathbf{A} \mathbf{u}_m + b_1 \mathbf{A} \mathbf{v}_1 + b_2 \mathbf{A} \mathbf{v}_2 + \dots + b_p \mathbf{A} \mathbf{v}_p = \mathbf{A} \mathbf{0}$$

$$\Rightarrow a_1 \lambda \mathbf{u}_1 + a_2 \lambda \mathbf{u}_2 + \dots + a_m \lambda \mathbf{u}_m + b_1 \mu \mathbf{v}_1 + b_2 \mu \mathbf{v}_2 + \dots + b_p \mu \mathbf{v}_p = \mathbf{0}.$$
 (3)

Adding $-\mu$ times of Equation (2) to Equation (3), we have

$$a_1(\lambda_1 - \mu)\boldsymbol{u}_1 + a_2(\lambda_2 - \mu)\boldsymbol{u}_2 + \dots + a_m(\lambda_m - \mu)\boldsymbol{u}_m = \mathbf{0}.$$

Since u_1, u_2, \ldots, u_m are linearly independent,

$$a_1(\lambda_1 - \mu) = a_2(\lambda_2 - \mu) = \dots = a_m(\lambda_m - \mu) = 0.$$

As $\mu \neq \lambda_i$, $a_i = 0$ for all $1 \leq i \leq m$.

Plugging $a_i = 0$ into (2), we have

$$b_1\boldsymbol{v}_1+b_2\boldsymbol{v}_2+\cdots+b_p\boldsymbol{v}_p=\boldsymbol{0}.$$

Since v_1, v_2, \ldots, v_p are linearly independent, we have $b_j = 0$ for all $1 \le j \le p$. Therefore $\{u_1, u_2, \ldots, u_m, v_1, v_2, \ldots, v_p\}$ is linearly independent.