## **Eigenvalue eigenvector**

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Linear algebra- II (IC152)

### Singular matrix

We first recall the following theorem:

#### **Theorem**

Let  $A = [a_{ij}]$  be an  $n \times n$  matrix with eigenvalues  $\lambda_1, \lambda_2, \dots, \lambda_n$ , not necessarily distinct. Then  $\det(A) = \prod_{i=1}^n \lambda_i$  and  $tr(A) = \sum_{i=1}^n a_{ii} = \sum_{i=1}^n \lambda_i$ .

As a consequence of the above Theorem, we will describe the following corollary

### Corollary

Suppose A is a singular matrix. Then 0 is an eigen value of A.

#### **Theorem**

If  $\lambda_1, \lambda_2, \ldots, \lambda_k$  are distinct eigenvalues of a matrix A with corresponding eigenvectors  $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_k$ , then the set  $\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_k\}$  is linearly independent.

### **Outline of the proof**

- The proof is by induction on the number m of eigenvalues. The result is obviously true if m=1 as the corresponding eigenvector is non-zero and we know that any set containing exactly one non-zero vector is linearly independent.
- Let the result be true for m,  $1 \le m < k$ . We prove the result for m + 1. We consider the equation

$$c_1 x_1 + c_2 x_2 + \dots + c_{m+1} x_{m+1} = \mathbf{0}$$
 (1)

for the unknowns  $c_1, c_2, \ldots, c_{m+1}$ .

We have

$$\mathbf{0} = A\mathbf{0}$$

$$= A(c_1x_1 + c_2x_2 + \dots + c_{m+1}x_{m+1})$$

$$= c_1Ax_1 + c_2Ax_2 + \dots + c_{m+1}Ax_{m+1}$$

$$= c_1\lambda_1x_1 + c_2\lambda_2x_2 + \dots + c_{m+1}\lambda_{m+1}x_{m+1}.$$
 (2)

### Outline of the proof cont.

From Equations (1) and (2), we get

$$c_2(\lambda_2 - \lambda_1)\mathbf{x}_2 + c_3(\lambda_3 - \lambda_1) + \cdots + c_{m+1}(\lambda_{m+1} - \lambda_1)\mathbf{x}_{m+1} = \mathbf{0}.$$

 This is an equation in m eigenvectors. So, by the induction hypothesis, we have

$$c_i(\lambda_i - \lambda_1) = 0$$
 for  $2 \le i \le m + 1$ .

- But the eigenvalues are distinct implies  $\lambda_i \lambda_1 \neq 0$  for  $2 \leq i \leq m+1$ . We therefore get  $c_i = 0$  for  $2 \leq i \leq m+1$ .
- Also,  $\mathbf{x}_1 \neq \mathbf{0}$  and therefore (1) gives  $c_1 = 0$ .
- Thus, we have the required result.

### Distinct eigenvalue and eigenvector of a matrix

We are thus lead to the following important corollary.

### **Corollary**

The eigenvectors corresponding to distinct eigenvalues of an  $n \times n$  matrix A are linearly independent.

#### **Motivation**

- Let A be a square matrix of order n and let  $T_A : \mathbb{F}^n \longrightarrow \mathbb{F}^n$  be the corresponding linear transformation.
- We ask the question "does there exist a basis  $\mathcal{B}$ " of  $\mathbb{F}^n$  such that  $T_A[\mathcal{B},\mathcal{B}]$ , the matrix of the linear transformation  $T_A$ , is in the simplest possible form."
- We know that, the simplest form for a matrix is the identity matrix and the diagonal matrix.
- We show that for a certain class of matrices A, we can find a basis  $\mathcal{B}$  such that  $T_A[\mathcal{B},\mathcal{B}]$  is a diagonal matrix, consisting of the eigenvalues of A.
- This is equivalent to saying that A is similar to a diagonal matrix.
   To show the above, we need the following definition.

### **Matrix Diagonalisation**

### **Definition (Matrix Diagonalisation)**

A matrix A is said to be diagonalisable if there exists a non-singular matrix P such that  $P^{-1}AP$  is a diagonal matrix.

#### Remark

Let A be an  $n \times n$  diagonalisable matrix with eigenvalues  $\lambda_1, \lambda_2, \ldots, \lambda_n$ . By definition, A is similar to a diagonal matrix D. Observe that  $D = \operatorname{diag}(\lambda_1, \lambda_2, \ldots, \lambda_n)$  as similar matrices have the same set of eigenvalues and the eigenvalues of a diagonal matrix are its diagonal entries.

### **Example 1**

- Let  $A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$ .
- Consider  $P = \begin{bmatrix} 1 & 1 \\ 1 & -1 \end{bmatrix}$ . Note that  $\det P = -2 \neq 0$ . Hence, P is invertible.
- Observe that  $P^{-1} = \frac{1}{2} \begin{bmatrix} -1 & -1 \\ -1 & 1 \end{bmatrix}$ .
- $AP = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} = \begin{pmatrix} 1 & -1 \\ 1 & 1 \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix} = PD.$
- Since *P* is invertible, we get  $P^{-1}AP = D$ .

### **Example 2**

- Let  $A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$ .
- We will show that there does not exist an invertible matrix P such that  $P^{-1}AP = D$ .
- We will show it by contradiction. Suppose there exist an invertible matrix P such that  $P^{-1}AP = D$ , that is,

$$P^{-1}AP = \begin{bmatrix} d_1 & 0 \\ 0 & d_2 \end{bmatrix} = D$$

which is equivalent to say that  $A = P \begin{bmatrix} d_1 & 0 \\ 0 & d_2 \end{bmatrix} P^{-1}$ .

Also,

$$A^{2} = P \begin{bmatrix} d_{1}^{2} & 0\\ 0 & d_{2}^{2} \end{bmatrix} P^{-1}.$$
 (3)

### Example 2 cont.

Note that

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

• From (3) and (4), we have

$$P^{-1}\left(\begin{smallmatrix}0&0\\0&0\end{smallmatrix}\right)P=\left(\begin{smallmatrix}d_1^2&0\\0&d_2^2\end{smallmatrix}\right),\,$$

which implies  $d_1 = d_2 = 0$ .

- This shows that  $P^{-1}AP = \mathbf{0}_{2\times 2}$ , which gives  $A = P \mathbf{0}_{2\times 2}P^{-1} = \mathbf{0}_{2\times 2}$ , which is a contradiction, because  $A = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \neq \mathbf{0}_{2\times 2}$ .
- This shows that A is not a diagonalizable matrix.

### Consequences of the rank-nullity theorem

The following are some of the consequences of the rank-nullity theorem. The proof is left as an exercise for the reader.

#### **Theorem**

The following are equivalent for an  $m \times n$  real matrix A.

- Rank (A) = k.
- There exist exactly k rows of A that are linearly independent.
- There exist exactly k columns of A that are linearly independent.
- There is a  $k \times k$  submatrix of A with non-zero determinant and every  $(k+1) \times (k+1)$  submatrix of A has zero determinant.
- The dimension of the range space of A is k.
- There is a subset of  $\mathbb{R}^m$  consisting of exactly k linearly independent vectors  $\mathbf{b}_1, \mathbf{b}_2, \dots, \mathbf{b}_k$  such that the system  $A\mathbf{x} = \mathbf{b}_i$  for  $1 \le i \le k$  is consistent.
- The dimension of the null space of A = n k.

### Splits over F

#### **Definition**

A polynomial f(t) in  $P(\mathbb{F})$  splits over  $\mathbb{F}$  if there are scalars  $c, a_1, \cdots, a_n$  (not necessarily distinct) in  $\mathbb{F}$  such that

$$f(t) = c(t - a_1) \cdots (t - a_n).$$

- For example,  $t^2 1 = (t+1)(t-1)$  splits over  $\mathbb{R}$ .
- But  $(t^2 + 1)(t 2)$  does not split over  $\mathbb{R}$ .
- However,  $(t^2 + 1)(t 2)$  splits over  $\mathbb{C}$ .
- If f(t) is the characteristic polynomial of any matrix over a field  $\mathbb{F}$ , then the statement that f(t) splits is understood to mean that it splits over  $\mathbb{F}$ .

### **Algebraic multiplicity**

#### **Theorem**

The characteristic polynomial of any diagonalizable matrix splits.

• From the above theorem, it is clear that if A is a  $n \times n$  diagonalizable matrix that fails to have distinct eigenvalues, the characteristic polynomial of A must have repeated zeros.

#### **Definition**

Let  $\lambda$  be an eigenvalue of a matrix A with characteristic polynomial f(t). The algebraic multiplicity of  $\lambda$  is the largest positive integer k for which  $(t-\lambda)^k$  is a factor of f(t).

### Diagonalisable

By using previous theorem, we will prove the following theorem. The following theorem states the necessary and sufficient condition for diagonalizability of a matrix.

#### **Theorem**

let A be an  $n \times n$  matrix. Then A is diagonalisable if and only if A has n linearly independent eigenvectors.

### **Outline of the proof**

Let A be diagonalisable. Then there exist matrices P and D such that

$$P^{-1}AP = D = \operatorname{diag}(\lambda_1, \lambda_2, \dots, \lambda_n).$$

Or equivalently, AP = PD.

• Let  $P = [\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n]$ . Then AP = PD implies that

$$A\mathbf{u}_i = d_i\mathbf{u}_i$$
 for  $1 \le i \le n$ .

- Since  $\mathbf{u}_i$  's are the columns of a non-singular matrix P, they are non-zero and so for  $1 \le i \le n$ , we get the eigenpairs  $(d_i, \mathbf{u}_i)$  of A.
- Since,  $\mathbf{u}_i$  's are columns of the non-singular matrix P, using Theorem (6), we get  $\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n$  are linearly independent.
- Thus we have shown that if A is diagonalisable then A has n linearly independent eigenvectors.

### Outline of the proof cont. Converse part

- Conversely, suppose A has n linearly independent eigenvectors  $\mathbf{u}_i, \ 1 \le i \le n$  with eigenvalues  $\lambda_i$ . Then  $A\mathbf{u}_i = \lambda_i \mathbf{u}_i$ .
- Let  $P = [\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n]$ . Since  $\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n$  are linearly independent, by Theorem (6), P is non-singular.
- Also,

$$AP = [A\mathbf{u}_1, A\mathbf{u}_2, \dots, A\mathbf{u}_n]$$

$$= [\lambda_1 \mathbf{u}_1, \lambda_2 \mathbf{u}_2, \dots, \lambda_n \mathbf{u}_n]$$

$$= [\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_n] \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ \vdots & \vdots & \dots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{bmatrix}$$

$$= PD.$$

Therefore the matrix A is diagonalisable.

As a consequence of the above theorem, we will prove the following lemma.

### Corollary

let A be an  $n \times n$  matrix. Suppose that the eigenvalues of A are distinct. Then A is diagonalisable.

### **Outline of the proof**

- As A is an n × n matrix, it has n eigenvalues. Since all the eigenvalues of A are distinct, by Corollary (4), the n eigenvectors are linearly independent.
- Hence, by Theorem (10), *A* is diagonalisable.

### Corollary

Let A be an  $n \times n$  matrix with  $\lambda_1, \lambda_2, \ldots, \lambda_k$  as its distinct eigenvalues and  $p(\lambda)$  as its characteristic polynomial. Suppose that for each  $i, \ 1 \le i \le k, \ (x - \lambda_i)^{m_i}$  divides  $p(\lambda)$  but  $(x - \lambda_i)^{m_i+1}$  does not divides  $p(\lambda)$  for some positive integers  $m_i$ . Then

A is diagonalisable if and only if  $\dim(\ker(A-\lambda_i I))=m_i$  for each  $i,\ 1\leq i\leq k$ .

Or equivalently

A is diagonalisable if and only if  $rank(A - \lambda_i I) = n - m_i$  for each  $i, 1 \le i \le k$ .

### **Outline of the proof**

- As A is diagonalisable, by Theorem (10), A has n linearly independent eigenvalues.
- Also,  $\sum\limits_{i=1}^k m_i = n$  as  $\deg(p(\lambda)) = n$  .
- Hence, for each eigenvalue  $\lambda_i$ ,  $1 \le i \le k$ , A has exactly  $m_i$  linearly independent eigenvectors.
- Thus, for each  $i, 1 \le i \le k$ , the homogeneous linear system  $(A \lambda_i I)\mathbf{x} = \mathbf{0}$  has exactly  $m_i$  linearly independent vectors in its solution set.
- Therefore,  $\dim (\ker(A \lambda_i I)) \ge m_i$ . Indeed  $\dim (\ker(A \lambda_i I)) = m_i$  for  $1 \le i \le k$  follows from a simple counting argument.

### Outline of the proof cont.

- Now suppose that for each i,  $1 \le i \le k$ ,  $\dim(\ker(A \lambda_i I)) = m_i$ .
- Then for each  $i, 1 \le i \le k$ , we can choose  $m_i$  linearly independent eigenvectors.
- Also by Corollary (4), the eigenvectors corresponding to distinct eigenvalues are linearly independent.
- Hence A has  $n = \sum_{i=1}^{k} m_i$  linearly independent eigenvectors.
- Hence by Theorem (10), *A* is diagonalisable.

### **Test for diagonalization**

Let A be  $n \times n$  matrix. Then A is diagonalisable if and only if both of the following conditions hold:

- The characteristic polynomial of *A* splits.
- For each eigenvalue  $\lambda$  of A, the multiplicity of  $\lambda$  equals  $n \text{rank}(A \lambda I)$ .

### **Example 1**

• Let 
$$A = \begin{bmatrix} 2 & 1 & 1 \\ 1 & 2 & 1 \\ 0 & -1 & 1 \end{bmatrix}$$
.

- Then  $det(A \lambda I) = (2 \lambda)^2 (1 \lambda)$ . Hence, A has eigenvalues 1, 2, 2.
- $A-2I=\begin{bmatrix}0&1&1\\1&0&1\\0&-1&-1\end{bmatrix}$  has rank 2, we see that  $3-\operatorname{rank}(A-\lambda I)=1$ , which is not multiplicity of 2.
- It is easily seen that  $(1,(1,0,-1)^t)$  and  $((2,(1,1,-1)^t)$  are the only eigenpairs.
- That is, the matrix *A* has exactly one eigenvector corresponding to the repeated eigenvalue 2.
- Hence, by Theorem (10), the matrix A is not diagonalisable.

### **Example 2**

- Let  $A = \begin{bmatrix} 2 & 1 & 1 \\ 1 & 2 & 1 \\ 1 & 1 & 2 \end{bmatrix}$ . Then  $\det(A \lambda I) = (4 \lambda)(1 \lambda)^2$ . Hence, A has eigenvalues 1, 1, 4.
- It can be easily verified that  $(1, -1, 0)^t$  and  $(1, 0, -1)^t$  correspond to the eigenvalue 1 and  $(1, 1, 1)^t$  corresponds to the eigenvalue 4.
- Note that the set  $\{(1,-1,0)^t,(1,0,-1)^t\}$  consisting of eigenvectors corresponding to the eigenvalue 1 are not orthogonal.
- This set can be replaced by the orthogonal set  $\{(1,0,-1)^t,(1,-2,1)^t\}$  which still consists of eigenvectors corresponding to the eigenvalue 1 as (1,-2,1)=2(1,-1,0)-(1,0,-1).
- Also, the set  $\{(1,1,1),(1,0,-1),(1,-2,1)\}$  forms a basis of  $\mathbb{R}^3$ . So, by Theorem (10), the matrix A is diagonalisable.
- Also, if  $U = \begin{bmatrix} \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{6}} \\ \frac{1}{\sqrt{2}} & 0 & \frac{-2}{\sqrt{6}} \\ \frac{1}{\sqrt{3}} & -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{6}} \end{bmatrix}$  is the corresponding unitary matrix then  $U^*AU = \text{diag}(4,1,1)$ .

- Observe that the matrix A is a symmetric matrix. In this case, the eigenvectors are mutually orthogonal.
- In general, for any  $n \times n$  real symmetric matrix A, there always exist n eigenvectors and they are mutually orthogonal. This result will be proved later.

# Thank You