### Linear Algebra

#### Lecture 9 - Diagonalizable Matrices and Application

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# Diagonal Matrix

#### Definition

The matrix  $A = [a_{ij}] \in M(n \times n; \mathbb{R})$  is called **diagonal** if  $a_{ij} = 0$  for any  $i \neq j$ , i.e.

$$A = \left[ \begin{array}{ccc} a_{11} & & 0 \\ & \ddots & \\ 0 & & a_{nn} \end{array} \right].$$

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### Example

The matrices

$$\left[\begin{array}{ccc} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{array}\right], \quad \left[\begin{array}{cccc} 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & -2 \end{array}\right]$$

are diagonal.



## Diagonal Matrix of Linear Endomorphism

### Proposition

Let  $\varphi \colon V \longrightarrow V$  be an endomorphism of vector space V and let  $\mathcal{A} = (v_1, \ldots, v_n)$  be an ordered basis of V. Then  $M(\varphi)_{\mathcal{A}} = [a_{ij}]$  is diagonal if and only if  $v_i$  is an eigenvector of  $\varphi$ . Moreover, in such case eigenvector  $v_i$  is associated to the eigenvalue  $a_{ii}$ , i.e.

$$\varphi(\mathbf{v}_i) = \mathbf{a}_{ii} \mathbf{v}_i.$$

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#### Proof.

 $(\Leftarrow)$  Assume each  $v_i$  is an eigenvector of  $\varphi$  associated to eigenvalue  $\alpha_i$ . Then

$$\varphi(v_i) = \alpha_i v_i = 0 v_1 + 0 v_2 + \ldots + 0 v_{i-1} + \alpha_i v_i + 0 v_{i+1} + \ldots + 0 v_n,$$

i.e. in the *i*-th column of the matrix  $M(\varphi)_{\mathcal{A}}$  there is  $\alpha_i$  in the *i*-th row and 0's elsewhere.



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$$(\Rightarrow)$$
 similar to the above

Let 
$$\varphi \colon \mathbb{R}^2 \longrightarrow \mathbb{R}^2$$
 be given by  $\varphi((x_1, x_2)) = (8x_1 + 10x_2, -3x_1 - 3x_2)$ . Then

$$M(\varphi)_{st} = \begin{bmatrix} 8 & 10 \\ -3 & -3 \end{bmatrix}, \ w_{\varphi}(\lambda) = \det \begin{bmatrix} 8 - \lambda & 10 \\ -3 & -3 - \lambda \end{bmatrix},$$

The characteristic polynomial is

$$w_{\varphi}(\lambda) = (8 - \lambda)(-3 - \lambda) + 30 = \lambda^2 - 5\lambda + 6 = (\lambda - 2)(\lambda - 3).$$

There are two eigenvalues  $\lambda_1=2,\lambda_2=3$ .

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The characteristic polynomial is  $w_{\varphi}(\lambda) = (8-\lambda)(-3-\lambda) + 30 = \lambda^2 - 5\lambda + 6 = (\lambda-2)(\lambda-3)$ . There are two eigenvalues  $\lambda_1 = 2, \lambda_2 = 3$ . In order to get corresponding eigenspaces solve

$$V_{(2)}$$
:  $\begin{bmatrix} 6 & 10 \\ -3 & -5 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \iff x_1 = -\frac{5}{3}x_2,$ 

i.e. 
$$V_{(2)} = \{(-\frac{5}{3}x_2, x_2) \in \mathbb{R}^2 \mid x_2 \in \mathbb{R}\} = \text{lin}((-5, 3))$$

$$V_{(3)}$$
:  $\begin{bmatrix} 5 & 10 \\ -3 & -6 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \iff x_1 = -2x_2,$ 

i.e. 
$$V_{(3)}=\{(-2x_2,x_2)\in\mathbb{R}^2\mid x_2\in\mathbb{R}\}=\inf((-2,1))$$

# Example (continued)

Recall,  $\varphi((x_1,x_2))=(8x_1+10x_2,-3x_1-3x_2)$ . The basis  $\mathcal{A}=((-5,3),(-2,1))$  of  $\mathbb{R}^2$  consists of eigenvectors and

$$M(\varphi)_{\mathcal{A}} = \left[ \begin{array}{cc} 2 & 0 \\ 0 & 3 \end{array} \right],$$

since

$$\varphi((-5,3)) = 2(-5,3) + 0(-2,1),$$
  
$$\varphi((-2,1)) = 0(-5,3) + 3(-2,1).$$

### Eigenvectors for Different Eigenvalues

#### Theorem

Let  $\alpha_1,\ldots,\alpha_k\in\mathbb{R}$  be pairwise distinct eigenvalues of the linear endomorphism  $\varphi\colon V\longrightarrow V$ . Let  $\mathcal{A}_i\subset V_{(\alpha_i)}$  be a finite set of linearly independent eigenvectors of  $\varphi$  associated to  $\alpha_i$  for  $i=1,\ldots,k$ . Then  $\mathcal{A}=\mathcal{A}_1\cup\ldots\cup\mathcal{A}_k$  is a set of linearly independent vectors.

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#### Proof.

For simplicity we assume that  $\mathcal{A}_i = \{v_i\}$ , i.e. each set  $\mathcal{A}_i$  contains one vector. Assume  $\gamma_1 v_1 + \gamma_2 v_2 + \ldots + \gamma_k v_k = 0$ . By applying  $\varphi$  to both sides we get  $\alpha_1 \gamma_1 v_1 + \alpha_2 \gamma_2 v_2 + \ldots + \alpha_k \gamma_k v_k = 0$ . Repeating this procedure we get a system of linear equations:

#### Vandermonde Determinant

One can check that the Vandermonde determinant

$$\det \left[ \begin{array}{ccccc} 1 & 1 & 1 & \dots & 1 \\ \alpha_1 & \alpha_2 & \alpha_3 & \dots & \alpha_k \\ \alpha_1^2 & \alpha_2^2 & \alpha_3^2 & \dots & \alpha_k^2 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \alpha_1^{k-1} & \alpha_2^{k-1} & \alpha_3^{k-1} & \dots & \alpha_k^{k-1} \end{array} \right] = \prod_{1 \leqslant i < j \leqslant k} (\alpha_j - \alpha_i)$$

is non-zero and hence the system  $\it U$  can be brought by elementary row operations to a reduced echelon form

$$U : \begin{cases} \gamma_1 v_1 & = 0 \\ \gamma_2 v_2 & = 0 \\ \vdots & \vdots \\ \gamma_k v_k & = 0 \end{cases}$$

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$$\gamma_1 v_1 + \ldots + \gamma_m v_m = 0,$$

where  $\gamma_i \neq 0$  involves the least number of vectors (perhaps after rearranging them). Then, by applying  $\varphi$  to both sides of the equation

$$\gamma_1 \alpha_1 v_1 + \ldots + \gamma_m \alpha_m v_m = 0.$$

By multiplying the first equation by  $\alpha_{\it m}$  and subtracting it from the latter

$$\gamma_1(\alpha_1 - \alpha_m)v_1 + \ldots + \gamma_{m-1}(\alpha_{m-1} - \alpha_m)v_{m-1} = 0,$$

we get a linear combination involving m-1 vectors, which leads to a contradiction.

### Corollary

Let V be a finite dimensional vector space. Let  $\alpha_1,\ldots,\alpha_k\in\mathbb{R}$  be pairwise distinct eigenvalues of the linear endomorphism  $\varphi\colon V\longrightarrow V$ . Then

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i) if  $v_1, \ldots, v_k \in V$  and  $\varphi(v_i) = \alpha_i v_i$ ,  $v_i \neq 0$  for  $i = 1, \ldots, k$  then the vectors  $v_1, \ldots, v_k$  are linearly independent,

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- ii)  $\dim V_{(\alpha_1)} + \dim V_{(\alpha_2)} + \ldots + \dim V_{(\alpha_k)} \leqslant \dim V$ ,

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- iii)  $\dim V_{(\alpha_1)} + \dim V_{(\alpha_2)} + \ldots + \dim V_{(\alpha_k)} = \dim V \iff there$  exist a basis of V consisting of eigenvectors of  $\varphi \iff the$  matrix of  $\varphi$  relative to some basis of V is diagonal.

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In the part iii) of the corollary the basis of V consists of the union of bases of  $V_{(\alpha_i)}$  for  $i=1,\ldots,k$ .



Let 
$$\varphi \colon \mathbb{R}^3 \longrightarrow \mathbb{R}^3$$
 be given by 
$$\varphi((x_1,x_2,x_3)) = (2x_1 - 2x_2 + x_3, 2x_2 + x_3, 4x_3). \text{ Then}$$
 
$$M(\varphi)_{st} = \begin{bmatrix} 2 & -2 & 1 \\ 0 & 2 & 1 \\ 0 & 0 & 4 \end{bmatrix}, \quad w_{\varphi}(\lambda) = (2-\lambda)^2(4-\lambda).$$

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The eigenvalues of  $\varphi$  are 2 and 4.

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$$V_{(2)}$$
:  $\begin{bmatrix} 0 & -2 & 1 \\ 0 & 0 & 1 \\ 0 & 0 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \iff x_2 = x_3 = 0,$ 

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$$V_{(4)}$$
:  $\begin{bmatrix} -2 & -2 & 1 \\ 0 & -2 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \iff x_1 = 0 \text{ and } x_3 = 2x_2,$ 

$$V_{(4)} = \{(0, x_2, 2x_2) \in \mathbb{R}^3 \mid x_2 \in \mathbb{R}\} = \mathsf{lin}((0, 1, 2))$$

# Example (continued)

$$V_{(2)} = \{(x_1, 0, 0) \in \mathbb{R}^3 \mid x_1 \in \mathbb{R}\} = \text{lin}((1, 0, 0))$$
 $V_{(4)} = \{(0, x_2, 2x_2) \in \mathbb{R}^3 \mid x_2 \in \mathbb{R}\} = \text{lin}((0, 1, 2))$ 
 $+ \dim V_{(4)} = 1 + 1 < 3 = \dim \mathbb{R}^3$ , therefore there is no  $\mathbb{R}^3$  such that matrix of  $\varphi$  relative to it is diagonal.

 $\dim V_{(2)} + \dim V_{(4)} = 1 + 1 < 3 = \dim \mathbb{R}^3$ , therefore there is no basis of  $\mathbb{R}^3$  such that matrix of  $\varphi$  relative to it is diagonal.

### Corollary

Let V be a finite dimensional vector space and let  $\dim V = n$ . If the endomorphism  $\varphi \colon V \longrightarrow V$  has n pairwise distinct eigenvalues then there exists a basis of V consisting of eigenvectors.

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Matrix  $A \in M(n \times n; \mathbb{R})$  is diagonalizable  $\iff$  there exists a basis of  $\mathbb{R}^n$  consisting of eigenvectors of the endomorphism  $\varphi \colon \mathbb{R}^n \longrightarrow \mathbb{R}^n$  given by the condition  $M(\varphi)_{\mathsf{st}} = A$ .

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Matrix 
$$A = \begin{bmatrix} 8 & 10 \\ -3 & -3 \end{bmatrix}$$
 is diagonalizable. Endomorphism  $\varphi((x_1, x_2)) = (8x_1 + 10x_2, -3x_1 - 3x_2)$  has two eigenvalues 2 and 3. We have computed  $V_{(2)} = \text{lin}((-5, 3))$  and  $V_{(3)} = \text{lin}((-2, 1))$ . Set  $\mathcal{A} = ((-5, 3), (-2, 1))$  and  $C = M(id)^{st}_{\mathcal{A}}$ .

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$$C=\begin{bmatrix}-5&-2\\3&1\end{bmatrix}, \quad C^{-1}=\begin{bmatrix}1&2\\-3&-5\end{bmatrix}$$

# Example (continued)

Matrix 
$$A = \begin{bmatrix} 2 & -2 & 1 \\ 0 & 2 & 1 \\ 0 & 0 & 4 \end{bmatrix}$$
 is not diagonalizable. There is no basis of  $\mathbb{R}^3$  consisting of eigenvalues of the endomorphism  $\varphi((x_1,x_2,x_3)) = (2x_1 - 2x_2 + x_3, 2x_2 + x_3, 4x_3)$ .

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## Application

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$$A = \begin{bmatrix} a_{11} & 0 \\ & \ddots & \\ 0 & & a_{nn} \end{bmatrix}$$
 be a diagonal matrix. Then

$$A^{m} = \begin{bmatrix} a_{11}^{m} & 0 \\ & \ddots & \\ 0 & a_{nn}^{m} \end{bmatrix} \text{ for any } m \in \mathbb{N}.$$

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 for any  $m \in \mathbb{N}$ .

### Remark

Note that this, in general, does not hold for non-diagonal matrices, for example  $\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}^2 = \begin{bmatrix} 1 & 2 \\ 0 & 1 \end{bmatrix}$  and  $1^2 \neq 2$ .

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$$A^{n} = \begin{bmatrix} -5 & -2 \\ 3 & 1 \end{bmatrix} \begin{bmatrix} 2^{n} & 0 \\ 0 & 3^{n} \end{bmatrix} \begin{bmatrix} 1 & 2 \\ -3 & -5 \end{bmatrix} =$$

$$= \begin{bmatrix} -5 \cdot 2^{n} & + & 2 \cdot 3^{n+1} & -5 \cdot 2^{n+1} & + & 10 \cdot 3^{n} \\ 3 \cdot 2^{n} & - & 3^{n+1} & 3 \cdot 2^{n+1} & - & 5 \cdot 3^{n} \end{bmatrix} =$$

$$= 2^{n} \begin{bmatrix} -5 & -10 \\ 3 & 6 \end{bmatrix} + 3^{n} \begin{bmatrix} 6 & 10 \\ -3 & -5 \end{bmatrix} =$$

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$$= \begin{bmatrix} -5 \cdot 2^n & + & 2 \cdot 3^{n+1} & -5 \cdot 2^{n+1} & + & 10 \cdot 3^n \\ 3 \cdot 2^n & - & 3^{n+1} & 3 \cdot 2^{n+1} & - & 5 \cdot 3^n \end{bmatrix} =$$

$$= 2^n \begin{bmatrix} -5 & -10 \\ 3 & 6 \end{bmatrix} + 3^n \begin{bmatrix} 6 & 10 \\ -3 & -5 \end{bmatrix} =$$

$$= 2^n \left( 3 \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} 8 & 10 \\ -3 & -3 \end{bmatrix} \right) + 3^n \left( -2 \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} 8 & 10 \\ -3 & -3 \end{bmatrix} \right) =$$

$$= (3 \cdot 2^n - 2 \cdot 3^n) I_2 + (-2^n + 3^n) A.$$

$$A = \begin{bmatrix} 8 & 10 \\ -3 & -3 \end{bmatrix},$$

$$A^{n} = (3 \cdot 2^{n} - 2 \cdot 3^{n})I + (-2^{n} + 3^{n})A.$$

Note that for n=2

$$A^2 = 5A - 6I,$$

we recover the characteristic polynomial  $w_A(\lambda) = \lambda^2 - 5\lambda + 6$ .

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Note that for n=2

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we recover the characteristic polynomial  $w_A(\lambda) = \lambda^2 - 5\lambda + 6$ . Since A and I are linearly independent it follows that

$$\lambda^n \equiv (-2^n + 3^n)\lambda + (3 \cdot 2^n - 2 \cdot 3^n) \pmod{w_A(\lambda)},$$

i.e. the polynomial

$$\lambda^{n} - [(-2^{n} + 3^{n})\lambda + (3 \cdot 2^{n} - 2 \cdot 3^{n})],$$

is divisible by the polynomial  $w_A(\lambda)$ .



## Determinant of a Diagonalizable Matrix

### Proposition

Let  $A \in M(n \times n; \mathbb{R})$  be a diagonalizable matrix and let  $\lambda_1, \ldots, \lambda_n \in \mathbb{R}$  denote the eigenvalues of A. Then

$$\det A = \lambda_1 \cdot \ldots \cdot \lambda_n.$$

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$$\det A = \lambda_1 \cdot \ldots \cdot \lambda_n$$
.

### Proof.

Let

$$D = \left[ \begin{array}{cccc} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & & \ddots & \vdots \\ 0 & 0 & \dots & \lambda_n \end{array} \right].$$

Then

$$\det A = w_A(0) = w_D(0) = \lambda_1 \cdot \ldots \cdot \lambda_n.$$



## Coefficients of Characteristic Polynomial

#### Remark

In general, for any matrix  $A \in M(n \times n; \mathbb{R})$ 

$$w_A(\lambda) = \sum_{i=0}^n (-1)^i \left( \sum_{\substack{J \subset \{1,\dots,n\} \\ \#J = n-i}} \det A_{J;J} \right) \lambda^i,$$

where if  $J = \{j_1, \dots, j_{n-i}\}$  and  $1 \leqslant j_1 < \dots < j_{n-i} \leqslant n$ 

$$\det A_{J;J} = \det A_{j_1,\ldots,j_{n-i};j_1,\ldots,j_{n-i}},$$

denotes a minor of order (n-i) (so called principal minor).

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denotes a minor of order (n-i) (so called principal minor).

In other words, the coefficient of  $\lambda^i$  is equal to  $(-1)^i$  times the sum of all principal minors of order (n-i).



### Proof.

If  $A(\lambda) = [a_{ij}(\lambda)]$  where  $a_{ij}(\lambda)$  are differentiable functions of variable  $\lambda$ , the **Jacobi formula** holds

$$\frac{\mathrm{d}}{\mathrm{d}\lambda}\det A(\lambda) = \mathsf{Tr}(\mathsf{adj}(A(\lambda))\frac{\mathrm{d}}{\mathrm{d}\lambda}A(\lambda)),$$

where  $\frac{\mathrm{d}}{\mathrm{d}\lambda}A(\lambda)=\left[\frac{\mathrm{d}}{\mathrm{d}\lambda}a_{ij}(\lambda)\right]$  and for  $B=\left[b_{ij}\right]$  the trace of matrix  $B\in M(n\times n;\mathbb{R})$  is equal to  $\mathrm{Tr}(B)=\sum_{i=1}^n b_{ii}$ .

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If  $A=[a_{ij}]\in M(n imes n;\mathbb{R})$  is a square matrix, by the Jacobi formula

$$\frac{\mathrm{d}}{\mathrm{d}\lambda} w_A(\lambda) = \mathsf{Tr}(\mathsf{adj}(A - \lambda I)(-I)) = -\sum_{\substack{J \subset \{1, \dots, n\} \\ \#J = n-1}} \mathsf{det}(A - \lambda I)_{J;J}.$$

Proof.

Using induction one can show that

$$\frac{\mathrm{d}^{i}}{\mathrm{d}\lambda^{i}}w_{A}(\lambda) = (-1)^{i}i! \sum_{\substack{J \subset \{1,\dots,n\} \\ \#J = n-i}} \det(A - \lambda I)_{J;J}.$$

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The claim follows from the Taylor formula, i.e.

$$w_A(\lambda) = \sum_{i=0}^n \frac{1}{i!} \frac{\mathrm{d}^i}{\mathrm{d}\lambda^i} w_A(0) \lambda^i.$$

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#### Remark

The Jacobi formula follows directly form the chain rule for total derivatives (note that  $\frac{\partial}{\partial a_{ij}} \det A = (-1)^{i+j} \det A_{ij}$  hence  $d(\det)_A = \operatorname{adj}(A)$ ).

The coefficients of characteristic polynomial are also symmetric functions of eigenvalues (permuting, i.e. changing the order of factors does not change the coefficients).

$$(\lambda - \lambda_1)(\lambda - \lambda_2) = \lambda^2 - (\lambda_1 + \lambda_2)\lambda + \lambda_1\lambda_2,$$

$$(\lambda - \lambda_1)(\lambda - \lambda_2)(\lambda - \lambda_3) = \lambda^3 - (\lambda_1 + \lambda_2 + \lambda_3)\lambda^2 + (\lambda_1\lambda_2 + \lambda_1\lambda_3 + \lambda_2\lambda_3)\lambda -$$

$$-\lambda_1\lambda_2\lambda_3,$$

$$(\lambda - \lambda_1)(\lambda - \lambda_2)(\lambda - \lambda_3)(\lambda - \lambda_4) = \lambda^4 - (\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4)\lambda^3 +$$

$$+(\lambda_1\lambda_2 + \lambda_1\lambda_3 + \lambda_1\lambda_4 + \lambda_2\lambda_3 + \lambda_2\lambda_4 + \lambda_3\lambda_4)\lambda^2 -$$

$$-(\lambda_1\lambda_2\lambda_3 + \lambda_1\lambda_2\lambda_4 + \lambda_1\lambda_3\lambda_4 + \lambda_2\lambda_3\lambda_4)\lambda + \lambda_1\lambda_2\lambda_3\lambda_4.$$

$$\vdots$$

## Elementary Symmetric Polynomials

### Definition

The m-th symmetric polynomial in variables  $x_1, \ldots, x_n$ , where  $m \ge 0$  (assume  $e_0 = 1$ ) is,

$$e_m = e_m(x_1, \dots, x_n) = \sum_{1 \le i_1 < i_2 < \dots < i_m \le n} x_{i_1} x_{i_2} \cdot \dots \cdot x_{i_m}.$$

# Elementary Symmetric Polynomials (continued)

### Proposition

The coefficients of the characteristic polynomial  $w_A$  of matrix  $A \in M(n \times n; \mathbb{C})$  are (up to a sign) elementary symmetric polynomials of the (complex) eigenvalues of A, i.e.

$$w_{A}(\lambda) = \sum_{j=0}^{n} (-1)^{n-j} e_{j}(\lambda_{1}, \ldots, \lambda_{n}) \lambda^{n-j}.$$

### Proof.

Omitted (use induction).

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<sup>&</sup>lt;sup>0</sup>cf. I. G. Macdonald *Symmetric Functions and Hall Polynomials*, Oxford

### **Partitions**

#### Definition

A partition  $\mu$  of a natural number  $n\in\mathbb{N}$  is any sequence of natural numbers  $\mu_1,\mu_2,\mu_3\dots$  such that

$$|\mu| = \mu_1 + \mu_2 + \mu_3 + \ldots = n,$$

and

$$\mu_1 \geqslant \mu_2 \geqslant \mu_3 \geqslant \ldots$$

The numbers  $\mu_1, \mu_2, \mu_3 \dots$  are called **parts** of  $\mu$ . The number of non-zero parts  $I(\mu)$  of  $\mu$  is called the **length** of  $\mu$ .

Cambridge 2001



<sup>&</sup>lt;sup>0</sup>alternatively cf. R. P. Stanley *Enumerative Combinatorics vol. 2*,

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### Example

(2,2,1,0,0) is a partition of the number 5 of length 3, i.e.  $|\mu|=5$  and  $I(\mu)=3$ . It is denoted alternatively as  $\mu=(1^12^23^0\ldots)$ .

<sup>&</sup>lt;sup>0</sup>alternatively cf. R. P. Stanley *Enumerative Combinatorics vol. 2*, Cambridge 2001

## Monomial Symmetric Polynomials

#### Definition

For any partition  $\mu=(1^{k_1}2^{k_2}3^{k_3}\dots)$  such that  $|\mu|=m$  and  $I(\mu)\leqslant n$  the m-th monomial symmetric polynomial  $m_\mu$  is given by the formula

$$m_{\mu} = m_{\mu}(x_1, \ldots, x_n) = \frac{1}{k_1! k_2! \ldots k_n!} \sum_{\sigma \in S_n} x_1^{\mu(\sigma(1))} x_2^{\mu(\sigma(2))} \cdot \ldots \cdot x_n^{\mu(\sigma(n))},$$

where  $S_n$  denotes the n—th symmetric group (i.e. the group of all permutations of the set  $\{1, \ldots, n\}$ ).

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### Example

Let  $\mu = (2, 1, 0)$  and n = 3, then

$$m_{\mu}(x_1, x_2, x_3) = x_1^2 x_2 + x_1^2 x_3 + x_1 x_2^2 + x_2^2 x_3 + x_1 x_3^2 + x_2 x_3^2.$$

# Monomial Symmetric Polynomials (continued)

#### Remark

The constant  $\frac{1}{k_1!k_2!...k_n!}$  is chosen to make coefficients of all monomials in  $m_\mu$  equal to 1. For example, let  $\mu=(1,1,0)$  and n=3, then

$$m_{\mu}(x_1, x_2, x_3) = x_1x_2 + x_1x_3 + x_2x_3.$$

For example, let  $\mu=(1,1,1)$  and n=3, then

$$m_{\mu}(x_1, x_2, x_3) = x_1 x_2 x_3.$$

Analogously for  $\mu = (2,0,0)$  and n = 3

$$m_{\mu}(x_1, x_2, x_3) = x_1^2 + x_2^2 + x_3^2.$$

## Complete Symmetric Polynomials

### Definition

For any  $m \ge 0$  the m-th complete symmetric polynomial  $h_m$  in variables  $x_1, \ldots, x_n$  is given by the formula

$$h_m = h_m(x_1, \ldots, x_n) = \sum_{|\mu|=m} m_{\mu}(x_1, \ldots, x_n).$$

We set  $h_0 = 1$  and  $h_m = 0$  for any m > n.

## Complete Symmetric Polynomials

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We set  $h_0 = 1$  and  $h_m = 0$  for any m > n.

Example

Let n=3, then

$$h_1(x_1,x_2,x_3)=x_1+x_2+x_3,$$

$$h_2(x_1,x_2,x_3) = \mu_{(2,0,0)} + \mu_{(1,1,0)} = x_1^2 + x_2^2 + x_3^2 + x_1x_2 + x_1x_3 + x_2x_3.$$

The polynomial  $h_m$  is sum of all monomials in variables  $x_1, \ldots, x_n$  of degree m.



## Power Symmetric Polynomials

#### Definition

For any  $m \ge 1$  the m-th power symmetric polynomial  $p_m$  in variables  $x_1, \ldots, x_n$  is given by the formula

$$p_m = p_m(x_1, \ldots, x_n) = m_{(1^m)} = x_1^m + \ldots + x_n^m.$$

We set  $p_0 = n$ .

## Power Symmetric Polynomials

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We set  $p_0 = n$ .

Example

For m=2 and n=3

$$p_2(x_1, x_2, x_3) = x_1^2 + x_2^2 + x_3^2.$$

## Symmetric Polynomials

### Definition

Polynomial  $P(x_1, ..., x_n) \in \mathbb{C}[x_1, ..., x_n]$  is **symmetric**, if for any  $\sigma \in S_n$ 

$$P(x_{\sigma(1)},\ldots,x_{\sigma(n)})=P(x_1,\ldots,x_n).$$

### Proposition

Any symmetric polynomial in n variables is a polynomial of  $h_1, \ldots, h_n$  (resp. of  $p_1, \ldots, p_n$ , resp. of  $e_1, \ldots, e_n$ ).

#### Proof.

Omitted.

### Newton Identities

Let

$$E(t) = (1+x_1t)(1+x_2t)\cdots(1+x_nt) = 1+e_1t+e_2t^2+\cdots+e_nt^n =$$

$$= \sum_{m=0}^{n} e_m(x_1,\ldots,x_n)t^m,$$

be the generating function for the elementary symmetric polynomials. Similarly, let

$$H(t) = \frac{1}{1 - x_1 t} \cdot \frac{1}{1 - x_2 t} \cdot \dots \cdot \frac{1}{1 - x_n t} =$$

$$= (1 + x_1 t + x_1^2 t^2 + \dots)(1 + x_2 t + x_2^2 t^2 + \dots) \cdot \dots \cdot (1 + x_n t + x_n^2 t^2 + \dots) =$$

$$= 1 + h_1 t + h_2 t^2 + \dots = \sum_{m=0}^{\infty} h_m(x_1, \dots, x_n) t^m.$$

$$P(t) = \frac{x_1}{1 - tx_1} + \frac{x_2}{1 - tx_2} + \dots + \frac{x_n}{1 - tx_n} = p_1 + p_2 t + p_3 t + \dots =$$

$$= \sum_{m=0}^{\infty} p_{m+1}(x_1, \dots, x_n) t^m.$$

## Newton Identities (continued)

The following (easy to check) equations hold

$$H(t)E(-t) = 1,$$

$$P(t) = \frac{H'(t)}{H(t)},$$

$$P(-t) = \frac{E'(t)}{E(t)},$$

giving raise (by the uniqueness of the Taylor expansion, comparing the coefficients at  $t^k$ ) to the following identities, respectively

$$\sum_{m=0}^{k} (-1)^m e_m h_{m-k} = 0, \quad \text{for} \quad k \geqslant 1$$

$$\sum_{m=0}^{k} h_m p_{k-m+1} = (k+1) h_{k+1}, \quad \text{for} \quad k \geqslant 0,$$

$$\sum_{m=0}^{k} (-1)^{k-m} e_m p_{k-m+1} = (k+1) e_{k+1}, \quad \text{for} \quad k \geqslant 0.$$

# Newton Identities (continued)

Usually, those identities are written in a slightly different but equivalent (simple exercise) way

$$\sum_{m=0}^{k} (-1)^m e_m h_{m-k} = 0, \quad \text{for } k \geqslant 1$$

$$\sum_{m=1}^{k} h_{k-m} p_m = k h_k, \quad \text{for } k \geqslant 1,$$

$$\sum_{m=1}^{k} (-1)^{m-1} e_{k-m} p_m = k e_k, \quad \text{for } k \geqslant 1.$$

Moreover, it is possible to express  $e_m$ 's and  $h_m$ 's solely in terms of  $p_m$ 's which lead for example to formulas for the coefficients of the characteristic polynomial  $w_A$  in terms of  $\operatorname{tr}(A), \operatorname{tr}(A^2), \ldots, \operatorname{tr}(A^n)$  (see Faddeev–LeVerrier algorithm).

# Newton Identities (continued)

## Proposition

The following formulas hold

$$h_m(x_1,\ldots,x_n) = \sum_{\substack{|\mu|=m\\ \mu=(1^{k_1}2^{k_2}\ldots)}} \frac{1}{\prod_j j^{k_j} k_j!} p_{\mu},$$

$$e_m(x_1,\ldots,x_n) = \sum_{\substack{|\mu|=m\\ \mu=(1^{k_1}2^{k_2}\ldots)}} (-1)^{m-I(\mu)} \frac{1}{\prod_j j^{k_j} k_j!} p_{\mu_1} p_{\mu_2} \cdot \ldots,$$

where

$$p_{\mu}=p_{\mu_1}p_{\mu_2}\cdot\ldots$$

### Proof.

Omitted. Observe that the identities do not depend on n (i.e. the number of variables).

## Newton Identities – Example

$$\begin{split} h_1 &= p_{(1)} = p_1, \\ h_2 &= p_{(2)} + p_{(1,1)} = p_{(1^02^1...)} + p_{(1^22^0...)} = \\ &= \frac{1}{1^0 \cdot 0! \cdot 2^1 \cdot 1!} p_2 + \frac{1}{1^2 \cdot 2!} p_1 p_1 = \frac{1}{2} (p_1^2 + p_2), \\ h_3 &= p_{(3)} + p_{(2,1)} + p_{(1,1,1)} = p_{(1^02^03^1...)} + p_{(1^12^1...)} + p_{(1^3...)} = \\ &= \frac{1}{3^1 1!} p_3 + \frac{1}{1^1 \cdot 1! \cdot 2^1 \cdot 1!} p_2 p_1 + \frac{1}{1^3 3!} p_1 p_1 p_1 = \frac{1}{3} p_3 + \frac{1}{2} p_1 p_2 + \frac{1}{6} p_1^3, \end{split}$$

## Newton Identities - Example

$$\begin{split} e_1 &= p_{(1)} = p_1, \\ e_2 &= -p_{(2)} + p_{(1,1)} = -p_{(1^02^1\dots)} + p_{(1^22^0\dots)} = \\ &= \frac{1}{1^0 \cdot 0! \cdot 2^1 \cdot 1!} p_2 + \frac{1}{1^2 \cdot 2!} p_1 p_1 = \frac{1}{2} (p_1^2 - p_2), \\ e_3 &= p_{(3)} - p_{(2,1)} + p_{(1,1,1)} = p_{(1^02^03^1\dots)} - p_{(1^12^1\dots)} + p_{(1^3\dots)} = \\ &= \frac{1}{3^11!} p_3 - \frac{1}{1^1 \cdot 1! \cdot 2^1 \cdot 1!} p_2 p_1 + \frac{1}{1^33!} p_1 p_1 p_1 = \frac{1}{3} p_3 - \frac{1}{2} p_1 p_2 + \frac{1}{6} p_1^3, \\ &\vdots \end{split}$$

# Newton Identities – Example (continued)

Three numbers  $x, y, z \in \mathbb{R}$  satisfy the following system of equations

$$\begin{cases} x + y + z = 2, \\ x^2 + y^2 + z^2 = 6, \\ x^3 + y^3 + z^3 = 8. \end{cases}$$

Determine xyz. The problem can be solved using the identity

$$e_3 = \frac{1}{3}p_3 - \frac{1}{2}p_1p_2 + \frac{1}{6}p_1^3,$$

that is

$$xyz = \frac{1}{3} \cdot 8 - \frac{1}{2} \cdot 2 \cdot 6 + \frac{1}{6} \cdot 2^3 =$$
$$= \frac{8}{3} - 6 + \frac{4}{3} = -2.$$

In fact, x = 1, y = 2, z = -1 (up to a permutation).

## Schur Polynomials

For any monomial  $x^{\alpha}=x_1^{\alpha_1}x_2^{\alpha_2}\cdot\ldots\cdot x_n^{\alpha_n}$  define the antisymmetric (or skew–symmetric) function

$$a_{\alpha}(x_1,\ldots,x_n) = \sum_{\sigma \in S_n} \operatorname{sgn} \sigma(\sigma.x^{\alpha}),$$

where

$$\sigma.x^{\alpha} = x_{\sigma(1)}^{\alpha_1} x_{\sigma(2)}^{\alpha_2} \cdot \dots x_{\sigma(n)}^{\alpha_n}.$$

For example, if  $\alpha = (1, 2, 0)$  and n = 3 then

$$a_{\alpha}(x_1, x_2, x_3) = x_1 x_2^2 + x_2^2 x_3 + x_1 x_3^2 - x_1^2 x_2 - x_2^2 x_3 - x_1 x_3^2.$$



The alternative definition of the determinant implies that

$$a_{\alpha}(x_{1},...,x_{n}) = \det \begin{bmatrix} x_{1}^{\alpha_{1}} & x_{1}^{\alpha_{2}} & x_{1}^{\alpha_{3}} & \cdots & x_{1}^{\alpha_{n}} \\ x_{2}^{\alpha_{1}} & x_{2}^{\alpha_{2}} & x_{2}^{\alpha_{3}} & \cdots & x_{2}^{\alpha_{n}} \\ x_{3}^{\alpha_{1}} & x_{3}^{\alpha_{2}} & x_{3}^{\alpha_{3}} & \cdots & x_{3}^{\alpha_{n}} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{n}^{\alpha_{1}} & x_{n}^{\alpha_{2}} & x_{n}^{\alpha_{3}} & \cdots & x_{n}^{\alpha_{n}} \end{bmatrix}$$

From the properties of the determinant it follows that

$$a_{\alpha}(x_1,\ldots,x_i,\ldots,x_j,\ldots,x_n)=-a_{\alpha}(x_1,\ldots,x_j,\ldots,x_i,\ldots,x_n),$$

(i.e.  $a_lpha$  is alternating and hence antisymmetric) and that

$$a_{\alpha}=0$$
,

if some  $\alpha_i=\alpha_j$  for  $i\neq j$ . It follows that the polynomial  $a_\alpha$  is divisible by the polynomial  $x_i-x_j$  in the ring  $\mathbb{Z}[x_1,\ldots,x_n]$ . For example for  $\alpha=(1,2,0)$  and n=3

$$a_{\alpha}(x_1, x_2, x_3) = x_1 x_2^2 + x_2^2 x_3 + x_1 x_3^2 - x_1^2 x_2 - x_2^2 x_3 - x_1 x_3^2 =$$

$$= (x_1 - x_2)(-x_1 x_2 + x_1 x_3 + x_2 x_3 - x_3^2) =$$

$$= (x_2 - x_1)(x_3 - x_1)(x_3 - x_2).$$

Without the loss of generality one can assume that

$$\alpha_1 > \alpha_2 > \ldots > \alpha_n \geqslant 0.$$

This implies that  $\alpha_1\geqslant n-1,\alpha_2\geqslant n-2,\ldots$  therefore if  $\delta=(n-1,n-2,n-3,\ldots,2,1,0)$  then

$$\mu = \alpha - \delta$$
,

has non-negative components. Moreover

$$\mu_1 - \mu_2 = (\alpha_1 - (n-1)) - (\alpha_2 - (n-2)) = \alpha_1 - \alpha_2 - 1 \ge 0,$$
  

$$\mu_2 - \mu_3 = (\alpha_2 - (n-2)) - (\alpha_3 - (n-3)) = \alpha_2 - \alpha_3 - 1 \ge 0,$$
  
:

that is  $\mu$  is a partition. This can be reversed, that is for any partition  $\mu$ , the  $\alpha = \mu + \delta$  gives a non–zero function  $a_{\alpha}$ . Observe that  $a_{\delta}(x_1, \ldots, x_n)$  is the Vandermonde determinant.

### Definition

For any partition  $\mu$  and  $\delta=(n-1,n-2,\ldots,2,1,0)$  the Schur polynomial (in variables  $x_1,\ldots,x_n$ ) is the symmetric polynomial in  $\mathbb{Z}[x_1,\ldots,x_n]$  given by the formula

$$s_{\mu}=s_{\mu}(x_1,\ldots,x_n)=\frac{a_{\mu+\delta}}{a_{\delta}}.$$

### Remark

Schur polynomials for  $\mu$  such that  $|\mu|=m$  form a  $\mathbb{Z}-basis$  of the homogeneous symmetric polynomials of degree m. Schur polynomials play an important role in combinatorics, algebraic geometry, representation theory of the symmetric group, general linear group and the unitary group.

$$s_{\mu} = \frac{\det \begin{bmatrix} x_{1}^{\mu_{1}+(n-1)} & x_{1}^{\mu_{2}+(n-2)} & x_{1}^{\mu_{3}+(n-3)} & \cdots & x_{1}^{\mu_{n}+0} \\ x_{2}^{\mu_{1}+(n-1)} & x_{2}^{\mu_{2}+(n-2)} & x_{1}^{\mu_{3}+(n-3)} & \cdots & x_{2}^{\mu_{n}+0} \\ x_{3}^{\mu_{1}+(n-1)} & x_{3}^{\mu_{2}+(n-2)} & x_{1}^{\mu_{3}+(n-3)} & \cdots & x_{3}^{\mu_{n}+0} \\ \vdots & \vdots & & \vdots & & \vdots \\ x_{n}^{\mu_{1}+(n-1)} & x_{n}^{\mu_{2}+(n-2)} & x_{1}^{\mu_{3}+(n-3)} & \cdots & x_{n}^{\mu_{n}+0} \end{bmatrix}}{ \det \begin{bmatrix} x_{1}^{n-1} & x_{1}^{n-2} & x_{1}^{n-3} & \cdots & x_{1}^{0} \\ x_{2}^{n-1} & x_{1}^{n-2} & x_{1}^{n-3} & \cdots & x_{2}^{0} \\ x_{3}^{n-1} & x_{3}^{n-2} & x_{3}^{n-3} & \cdots & x_{n}^{0} \end{bmatrix}}$$

# Schur Polynomials – Example

$$\delta = (2, 1, 0)$$

$$s_{\delta} = -(x_{2} - x_{1})(x_{3} - x_{1})(x_{3} - x_{2})$$

$$s_{(2,0,0)}(x_{1}, x_{2}, x_{3}) = \frac{1}{s_{\delta}} \det \begin{bmatrix} x_{1}^{4} & x_{1}^{1} & x_{1}^{0} \\ x_{2}^{4} & x_{2}^{1} & x_{2}^{0} \\ x_{3}^{4} & x_{3}^{1} & x_{3}^{0} \end{bmatrix} =$$

$$= \frac{1}{s_{\delta}} \left( -(x_{2} - x_{1}) \cdot (x_{3} - x_{2})(x_{3}^{2} + x_{2}x_{3} + x_{1}x_{3} + x_{2}^{2} + x_{1}x_{2} + x_{1}^{2}) \right) =$$

$$= x_{1}^{2} + x_{2}^{2} + x_{3}^{2} + x_{1}x_{2} + x_{1}x_{3} + x_{2}x_{3}.$$

# Schur Polynomials - Another Example

$$\delta = (2, 1, 0)$$

$$s_{\delta} = -(x_2 - x_1)(x_3 - x_1)(x_3 - x_2)$$

$$s_{(1,1,0)}(x_1, x_2, x_3) = \frac{1}{s_{\delta}} \det \begin{bmatrix} x_1^3 & x_1^2 & x_1^0 \\ x_2^3 & x_2^2 & x_2^0 \\ x_3^3 & x_3^2 & x_3^0 \end{bmatrix} =$$

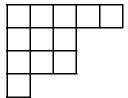
$$= \frac{1}{s_{\delta}} \left( -(x_2 - x_1)(x_3 - x_1)(x_3 - x_2)(x_2 x_3 + x_1 x_3 + x_1 x_2) \right) =$$

$$= x_1 x_2 + x_1 x_3 + x_2 x_3.$$

## Semistandard Young Tableau

### Definition

For any partition  $\mu$  a semistandard Young tableau T of shape  $\mu$  is a way of placing numbers into the diagram ( $\mu_1$  boxes in the first row,  $\mu_2$  in the second, etc.)



#### such that

- i) numbers in rows are weakly increasing (from left to right),
- ii) numbers in columns are strictly increasing (top to down).

# Semistandard Young Tableau

### Definition

The set  $SSYT_{\mu}$  is the set of all semistandard Young tableaux and  $SSYT_{\mu}(n)$  is the set of all semistandard Young tableuax with entries not greater than n. For any  $T \in SSYT_{\mu}(n)$ 

$$x^{T} = x_1^{\#1's} x_2^{\#2's} \cdot \ldots \cdot x_n^{\#n's},$$

that  $x_j$  is raised to the number of occurrence of j in T.

¹cf. B. E. Sagan, The Symmetric Group, Springer 2001 → → ◆ ≥ → ◆ ≥ → ◆ ∞ ◆

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$$x^{T} = x_1^{\#1's} x_2^{\#2's} \cdot \ldots \cdot x_n^{\#n's},$$

that  $x_i$  is raised to the number of occurrence of j in T.

## Proposition

$$s_{\mu}(x_1,\ldots,x_n) = \sum_{T \in SSYT_{\mu}(n)} x^T.$$

## Proof.

Omitted <sup>1</sup>

¹cf. B. E. Sagan, *The Symmetric Group*, Springer 2001 → → ◆ ≥ → ◆ ≥ → ◆ ∞ ◆

# Semistandard Young Tableau - Example

$$\mu = (2,0,0), \quad n = 3,$$

$$SSYT_{\mu}(n) = \left\{ \boxed{1} \ \boxed{1}, \boxed{2} \ 2, \boxed{3} \ \boxed{3}, \boxed{1} \ 2, \boxed{1} \ \boxed{3}, \boxed{2} \ \boxed{3} \right\},$$

$$s_{\mu} = x_1^2 + x_2^2 + x_3^2 + x_1x_2 + x_1x_3 + x_2x_3.$$

$$\mu = (1,1,0), \quad n = 3,$$

$$SSYT_{\mu}(n) = \left\{ \begin{array}{|c|c|c} 1 \\ \hline 2 \end{array}, \begin{array}{|c|c|c} 1 \\ \hline 3 \end{array}, \begin{array}{|c|c|c} 2 \\ \hline 3 \end{array} \right\},$$

$$s_{\mu} = x_{1}x_{2} + x_{1}x_{3} + x_{2}x_{3}.$$

## Pieri's Formula

## Proposition

$$s_{\mu}s_{(m)}=\sum_{
u}s_{
u},$$

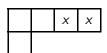
where the sum is over all paritions  $\nu$  obtained from  $\mu$  by adding m boxes but no two in a single column.

### Proof.

Omitted.

## Pieri's Formula – Example

$$s_{(2,1)}s_{(2)}=s_{(4,1)}+s_{(3,2)}+s_{(3,1,1)}+s_{(2,2,1)},\\$$









## Symmetric Matrix – Spectral Theorem

### Definition

Matrix  $A \in M(n \times n; \mathbb{R})$  is called **symmetric** if  $A^{T} = A$ .

## Proposition

Let  $A \in M(n \times n; \mathbb{R})$  be a symmetric matrix. Then A is diagonalizable.

## Symmetric Matrix – Spectral Theorem

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## Proposition

Let  $A \in M(n \times n; \mathbb{R})$  be a symmetric matrix. Then A is diagonalizable.

Moreover there exists an **orthogonal** basis of  $\mathbb{R}^n$  consisting of eigenvectors of the endomorphism  $M(\varphi)_{st}=A$ , i.e. vectors of that basis are pairwise perpendicular.

Let

$$A = \begin{bmatrix} 1 & 2 & 0 \\ 2 & -2 & 0 \\ 0 & 0 & -3 \end{bmatrix}.$$

Then

$$w_{A}(\lambda) = -(\lambda + 3)[(1 - \lambda)(-2 - \lambda) - 4] = -(\lambda + 3)^{2}(\lambda - 2),$$
 
$$V_{(-3)} = \lim((-1, 2, 0), (0, 0, 1)),$$
 
$$V_{(2)} = \lim((2, 1, 0)),$$

and the eigenvectors are pairwise perpendicular.

# Minimal Polynomial

### Definition

Let  $A \in M(n \times n; \mathbb{R})$ . The minimal polynomial  $\mu_A$  of the matrix A is a non-zero monic polynomial with real coefficients of the least degree such that  $\mu_A(A) = 0$ .

Equivalently, the minimal polynomial of  $\boldsymbol{A}$  is the non-zero monic polynomial of the least degree which image under the map

$$\mathbb{R}[x] \ni P(x) \mapsto P(A) \in M(n \times n; \mathbb{R}),$$

is the zero matrix (or which divides each  $P(x) \in \mathbb{R}[x]$  with P(A) = 0).

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is the zero matrix (or which divides each  $P(x) \in \mathbb{R}[x]$  with P(A) = 0).

By the Cayley-Hamilton Theorem the minimal polynomial of A divides the characteristic polynomial of A, i.e.  $\mu_A \mid w_A$ .



# Minimal Polynomial

#### Remark

The degree of the minimal polynomial  $\mu_A$  is equal to the smallest number  $m \geqslant 1$  such that

$$A^m \in \mathsf{lin}(A^{m-1},\ldots,A^1,A^0),$$

and if

$$A^{m} = \alpha_{m-1}A^{m-1} + \ldots + \alpha_{1}A^{1} + \alpha_{0}A^{0},$$

for some  $\alpha_i \in \mathbb{R}$ , then

$$\mu_A(\lambda) = \lambda^m - (\alpha_{m+1}\lambda^{m-1} + \ldots + \alpha_1\lambda + \alpha_0).$$

Let  $A=\begin{bmatrix}8&10\\-3&-3\end{bmatrix}$ . Then  $w_A(\lambda)=(\lambda-2)(\lambda-3)$  and the only monic divisors of  $w_A$  are  $w_A,\lambda-2,\lambda-3$  and 1. Since A is not a diagonal matrix then  $\mu_A=w_A$ .

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Let 
$$B = \begin{bmatrix} 2 & -2 & 1 \\ 0 & 2 & 1 \\ 0 & 0 & 4 \end{bmatrix}$$
. Then  $w_B(\lambda) = (2 - \lambda)^2 (4 - \lambda)$ . Then only monic divisors of  $w_B$  are  $-w_B$ ,  $(\lambda - 2)^2$ ,  $\lambda - 2$ ,  $(\lambda - 2)(\lambda - 4)$ ,

 $\lambda-4$  and 1. It can be checked that  $\mu_B=-w_B$ .

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only monic divisors of  $w_B$  are  $-w_B$ ,  $(\lambda-2)^2$ ,  $\lambda-2$ ,  $(\lambda-2)(\lambda-4)$ ,  $\lambda-4$  and 1. It can be checked that  $\mu_B=-w_B$ . Equivalently, the matrix

$$B^2 = \left[ \begin{array}{cccc} 4 & -8 & 4 \\ 0 & 4 & 6 \\ 0 & 0 & 16 \end{array} \right],$$

is not a linear combination of matrices B and  $I_3$ .

# Minimal Polynomials of Similar Matrices

Proposition

Let  $A, B \in M(n \times n; \mathbb{R})$  be similar matrices. Then  $\mu_A = \mu_B$ .

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### Proof.

If  $A=C^{-1}BC$  then  $0=\mu_A(A)=C^{-1}\mu_A(B)C$  therefore  $\mu_A(B)=0$ . By definition  $\mu_B\mid \mu_A$  and analogously  $\mu_A\mid \mu_B$ . Since both polynomials are monic  $\mu_A=\mu_B$ .

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### Remark

Non-similar matrices can have the same minimal polynomials. For example

$$A = \left[ \begin{array}{ccc} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 2 \end{array} \right], \quad B = \left[ \begin{array}{ccc} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 2 \end{array} \right],$$

have the same minimal polynomial

$$\mu_A(\lambda) = \mu_B(\lambda) = (\lambda - 1)(\lambda - 2)$$

## Criterion for Diagonalizability

### **Theorem**

Let  $A \in M(n \times n; \mathbb{R})$ . Matrix A is diagonalizable if and only if the minimal polynomial of A factors as follows

$$\mu_A(\lambda) = (\lambda - \alpha_1)(\lambda - \alpha_2) \dots (\lambda - \alpha_k),$$

where  $\alpha_i \in \mathbb{R}$  and  $\alpha_i \neq \alpha_j$ , i.e.  $\alpha_i$  are pairwise distinct numbers.

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## Example

$$A = \begin{bmatrix} 8 & 10 \\ -3 & -3 \end{bmatrix}, \quad B = \begin{bmatrix} 2 & -2 & 1 \\ 0 & 2 & 1 \\ 0 & 0 & 4 \end{bmatrix}$$
$$\mu_A(\lambda) = (\lambda - 2)(\lambda - 3),$$
$$\mu_B(\lambda) = (\lambda - 2)^2(\lambda - 4).$$

Matrix A is diagonalizable and matrix B is not diagonalizable.



### Example

The minimal polynomial of matrix

$$C = \left[ \begin{array}{cc} 0 & -1 \\ 1 & 0 \end{array} \right],$$

is equal to its characteristic polynomial. The minimal polynomial has pairwise different complex roots so the matrix C diagonalizes over  $\mathbb C$  but not over  $\mathbb R$ .

### Corollary

Matrix  $A \in M(n \times n; \mathbb{C})$  of finite order (i.e.,  $A^m = I$  for some  $m \ge 1$ ) is diagonalizable (over  $\mathbb{C}$ ).

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The minimal polyomial of A divides the polynomial  $x^m-1$  which has only simple roots.

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## Warning

This theorem fails in positive characteristic, take say

$$\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} \in M(2 \times 2; \mathbb{F}_2).$$

#### Proof.

 $(\Rightarrow)$  Let  $D=C^{-1}AC$ , by the previous proposition  $\mu_A=\mu_D$ . Let  $\alpha_1,\ldots,\alpha_k\in\mathbb{R}$  be all pairwise distinct eigenvalues of matrix D. For any  $i=1,\ldots,k,\ v_i\in V_{(\alpha_i)}$ 

$$(D - \alpha_j I)v_i = (\alpha_i - \alpha_j)v_i$$
 for  $j = 1, \dots, k$ .

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It follows that for any  $i=1,\ldots,k,\ v_i\in V_{(\alpha_i)}$  and any  $m_1,\ldots,m_k\geqslant 0$ 

$$[(D-\alpha_1I)^{m_1}\dots(D-\alpha_kI)^{m_k}]v_i=(\alpha_i-\alpha_1)^{m_1}\dots(\alpha_i-\alpha_k)^{m_k}v_i.$$

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Since for any  $P(x) \in \mathbb{R}[x]$ 

$$P(D) = 0 \iff P(D)v_i = 0$$
 for any  $i = 1, ..., k, v_i \in V_{(\alpha_i)}$ 

it follows that the minimal polynomial  $\mu_{\mathcal{A}}(\lambda)$  is equal to

$$\mu_D(\lambda) = (\lambda - \alpha_1) \cdot \ldots \cdot (\lambda - \alpha_k), \quad \text{for all } \lambda \in \mathbb{R}$$

### Proof.

(⇐) Let

$$Q_i(\lambda) = \frac{\mu_A(\lambda)}{\lambda - \alpha_i}$$
 for  $i = 1, \dots, k$ .

Since

$$GCD(Q_1(\lambda),\ldots,Q_k(\lambda))=1,$$

there exist polynomials  $P_1, \ldots, P_k \in \mathbb{R}[x]$  such that

$$P_1(\lambda)Q_1(\lambda) + \ldots + P_k(\lambda)Q_k(\lambda) = 1.$$
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Since  $\mu_A \mid w_A$ , the numbers  $\alpha_1, \ldots, \alpha_k \in \mathbb{R}$  are eigenvalues of matrix A.

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#### Proof.

For any (column) vector  $v \in \mathbb{R}^n$  and any  $i=1,\ldots,k$ 

$$Q_i(A)v \in V_{(\alpha_i)},$$

because

$$\ker(A - \alpha_i I) = V_{(\alpha_i)}$$

and

$$(A - \alpha_i I)(Q_i(A))v = \mu_A(A)v = 0.$$

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Let  $v \in \mathbb{R}^n$  be any (column) vector. Substituting matrix A to the equation (??) and multiplying it by vector v on the right

$$v = Q_1(A) (P_1(A)v) + \ldots + Q_k(A) (P_k(A)v),$$

where

$$Q_i(A)(P_i(A)v) \in V_{(\alpha_i)}$$
 for  $i = 1, ..., k$ .



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Let  $\varphi\colon V\to V$  be an endomorphism and let  $W\subset V$  be subspace. Then W is an **invariant subspace** of  $\varphi$  if

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that is the minimal polynomial of  $\varphi|_W$  divides the minimal polynomial of  $\varphi$  hence it has simple roots.



### Proposition

Let  $\varphi_i \colon V \to V$  where  $i \in I$  be a family of diagonalisable endomorphisms. Then endomorphisms  $\varphi_i$  commute, i.e., for any  $i, j \in I$ 

$$\varphi_i\circ\varphi_j=\varphi_j\circ\varphi_i,$$

if and only if there exists a basis A of V such that matrices  $M(\varphi_i)_{\mathcal{A}}^A$  are diagonal for each  $i \in I$ , that is endomorphisms  $\varphi_i$  are simultaneously diagonalizable.

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#### Proof.

 $(\Leftarrow)$  if  $M(\varphi_i)_{\mathcal{A}}^{\mathcal{A}}$ ,  $M(\varphi_j)_{\mathcal{A}}^{\mathcal{A}}$  are diagonal then

$$M(\varphi_i)_{\mathcal{A}}^{\mathcal{A}}M(\varphi_j)_{\mathcal{A}}^{\mathcal{A}}=M(\varphi_j)_{\mathcal{A}}^{\mathcal{A}}M(\varphi_i)_{\mathcal{A}}^{\mathcal{A}}.$$

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if and only if there exists a basis A of V such that matrices  $M(\varphi_i)_{\mathcal{A}}^A$  are diagonal for each  $i \in I$ , that is endomorphisms  $\varphi_i$  are simultaneously diagonalizable.

#### Proof.

 $(\Leftarrow)$  if  $M(\varphi_i)_{\mathcal{A}}^{\mathcal{A}}$ ,  $M(\varphi_j)_{\mathcal{A}}^{\mathcal{A}}$  are diagonal then

$$M(\varphi_i)_{\mathcal{A}}^{\mathcal{A}}M(\varphi_j)_{\mathcal{A}}^{\mathcal{A}}=M(\varphi_j)_{\mathcal{A}}^{\mathcal{A}}M(\varphi_i)_{\mathcal{A}}^{\mathcal{A}}.$$

 $(\Rightarrow)$  induction of  $n = \dim V$ .

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 $(\Rightarrow)$  induction of  $n = \dim V$ . If n = 1 the statement is obvious.

# Simultaneously Diagonalizable Endomorphisms (continued)

#### Proof.

Assume there exists  $j \in I$  such that  $\dim V_{\varphi_j,(\lambda)} < \dim V$ , where  $\lambda \in \mathbb{R}$  is an eigenvalue of  $\varphi_j$  and  $W = V_{\varphi_j,(\lambda)}$  is an eigenspace of  $\varphi_j$  (otherwise each  $\varphi_i$  is a uniform scalling).

# Simultaneously Diagonalizable Endomorphisms (continued)

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$$\varphi_j(\varphi_i(\mathbf{v})) = \varphi_i(\varphi_j(\mathbf{v})) = \varphi_i(\lambda \mathbf{v}) = \lambda(\varphi_i(\mathbf{v})),$$

i.e.,

$$\varphi_i(V_{\varphi_j,(\lambda)}) \subset V_{\varphi_j,(\lambda)}.$$

# Simultaneously Diagonalizable Endomorphisms (continued)

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i.e.,

$$\varphi_i(V_{\varphi_j,(\lambda)}) \subset V_{\varphi_j,(\lambda)}.$$

The family  $\varphi_j|_W$  commute and each  $\varphi_j|_W$  is diagonalisable, therefore by the inductive assumption the family is simultaneously diagonalisable (by repeating the argument on each eigenspace of  $\varphi_i$ ).

### Vandermonde Determinant

### Proposition

For any  $\alpha_1, \ldots, \alpha_k \in \mathbb{R}$ 

$$\begin{split} V(\alpha_1,\dots,\alpha_k) &= \det \left[ \begin{array}{cccc} 1 & 1 & 1 & \dots & 1 \\ \alpha_1 & \alpha_2 & \alpha_3 & \dots & \alpha_k \\ \alpha_1^2 & \alpha_2^2 & \alpha_3^2 & \dots & \alpha_k^2 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \alpha_1^{k-1} & \alpha_2^{k-1} & \alpha_3^{k-1} & \dots & \alpha_k^{k-1} \end{array} \right] &= \\ &= \prod_{1 \leqslant i < j \leqslant k} (\alpha_j - \alpha_i). \end{split}$$

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#### Proof.

Proof by induction on k. For k = 2

$$V(\alpha_1, \alpha_2) = \det \begin{bmatrix} 1 & 1 \\ \alpha_1 & \alpha_2 \end{bmatrix} = \alpha_2 - \alpha_1.$$



Proof.

$$V(\alpha_1, \dots, \alpha_k) = \det \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ \alpha_1 & \alpha_2 & \alpha_3 & \dots & \alpha_k \\ \alpha_1^2 & \alpha_2^2 & \alpha_3^2 & \dots & \alpha_k^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \alpha_1^{k-1} & \alpha_2^{k-1} & \alpha_3^{k-1} & \dots & \alpha_k^{k-1} \end{bmatrix}^{r_k - \alpha_1 r_{k-1}} \stackrel{r_k - \alpha_1 r_{k-1}}{r_{k-1} - \alpha_1 r_{k-2}}$$

Proof.

$$V(\alpha_1,\dots,\alpha_k) = \det \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ \alpha_1 & \alpha_2 & \alpha_3 & \dots & \alpha_k \\ \alpha_1^2 & \alpha_2^2 & \alpha_3^2 & \dots & \alpha_k^2 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \alpha_1^{k-1} & \alpha_2^{k-1} & \alpha_3^{k-1} & \dots & \alpha_k^{k-1} \end{bmatrix}^{r_k - \alpha_1 r_{k-1}} \overset{r_{k-1} - \alpha_1 r_{k-2}}{r_{k-1} - \alpha_1 r_{k-2}}$$

$$= \det \begin{bmatrix} 1 & 1 & 1 & \dots & 1 \\ 0 & \alpha_2 - \alpha_1 & \alpha_3 - \alpha_1 & \dots & \alpha_k - \alpha_1 \\ 0 & \alpha_2^2 - \alpha_1 \alpha_2 & \alpha_3^2 - \alpha_1 \alpha_3 & \dots & \alpha_k^2 - \alpha_1 \alpha_k \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 0 & \alpha_2^{k-1} - \alpha_1 \alpha_2^{k-2} & \alpha_3^{k-1} - \alpha_1 \alpha_3^{k-2} & \dots & \alpha_k^{k-1} - \alpha_1 \alpha_k^{k-2} \end{bmatrix} =$$

#### Proof.

(by the Laplace formula along the first column)

$$=\det\begin{bmatrix} \alpha_2-\alpha_1 & \alpha_3-\alpha_1 & \dots & \alpha_k-\alpha_1\\ \alpha_2^2-\alpha_1\alpha_2 & \alpha_3^2-\alpha_1\alpha_3 & \dots & \alpha_k^2-\alpha_1\alpha_k\\ & \vdots & & & \\ \alpha_2^{k-1}-\alpha_1\alpha_2^{k-2} & \alpha_3^{k-1}-\alpha_1\alpha_3^{k-2} & \dots & \alpha_k^{k-1}-\alpha_1\alpha_k^{k-2} \end{bmatrix}=\\\\ =\det\begin{bmatrix} \alpha_2-\alpha_1 & \alpha_3-\alpha_1 & \dots & \alpha_k-\alpha_1\\ (\alpha_2-\alpha_1)\alpha_2 & (\alpha_3-\alpha_1)\alpha_3 & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k^{k-2} \end{bmatrix}=\\\\ =\det\begin{bmatrix} \alpha_2-\alpha_1 & \alpha_3-\alpha_1 & \dots & \alpha_k-\alpha_1\\ (\alpha_2-\alpha_1)\alpha_2 & (\alpha_3-\alpha_1)\alpha_3 & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k^{k-2} \end{bmatrix}=\\\\ =\det\begin{bmatrix} \alpha_2-\alpha_1 & \alpha_3-\alpha_1 & \dots & \alpha_k-\alpha_1\\ (\alpha_2-\alpha_1)\alpha_2 & (\alpha_3-\alpha_1)\alpha_3 & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k^{k-2} \end{bmatrix}=\\\\ =\det\begin{bmatrix} \alpha_1-\alpha_1 & \alpha_1-\alpha_1\\ (\alpha_2-\alpha_1)\alpha_2 & (\alpha_3-\alpha_1)\alpha_3 & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k^{k-2} \end{bmatrix}=\\\\ =\det\begin{bmatrix} \alpha_1-\alpha_1 & \alpha_1-\alpha_1\\ (\alpha_2-\alpha_1)\alpha_2 & (\alpha_3-\alpha_1)\alpha_3 & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_3-\alpha_1)\alpha_3^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_2-\alpha_1)\alpha_2^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_2-\alpha_1)\alpha_2^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & \\ (\alpha_2-\alpha_1)\alpha_2^{k-2} & (\alpha_2-\alpha_1)\alpha_2^{k-2} & \dots & (\alpha_k-\alpha_1)\alpha_k\\ & \vdots & & \\$$

(by dividing the j-th column by the factor  $(\alpha_{j+1} - \alpha_1)$ )

Proof.

$$= \prod_{1\leqslant 1 < j \leqslant k} (\alpha_j - \alpha_1) \det \left[ \begin{array}{cccc} 1 & 1 & \dots & 1 \\ \alpha_2 & \alpha_3 & \dots & \alpha_k \\ \alpha_2^2 & \alpha_3^2 & \dots & \alpha_k^2 \\ \vdots & \vdots & \ddots & \vdots \\ \alpha_2^{k-2} & \alpha_3^{k-2} & \dots & \alpha_k^{k-2} \end{array} \right] =$$

(by the inductive assumption)

$$= \prod_{1 \leq 1 < j \leq k} (\alpha_j - \alpha_1) \prod_{2 \leq i < j \leq k} (\alpha_j - \alpha_i) = V(\alpha_1, \dots, \alpha_k).$$

# Polynomial Interpolation

### Proposition

Let  $x_1, \ldots, x_{n+1} \in \mathbb{R}$  be pairwise distinct points, i.e.  $x_i \neq x_j$  for all  $1 \leq i < j \leq n+1$ . For any  $y_1, \ldots, y_{n+1} \in \mathbb{R}$  there exists a unique polynomial P(x) of degree at most n such that

$$P(x_i) = y_i \text{ for } i = 1, ..., n + 1.$$

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$$P(x_i) = y_i \text{ for } i = 1, ..., n + 1.$$

#### Proof.

The polynomial P(x) = y is given by the equation

#### Remark

Note that the coefficient of y is equal to  $(-1)^{n+1}V(x_1,\ldots,x_{n+1})$  hence it is non-zero.

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#### Remark

Equivalently,

$$P(x) = \sum_{i=1}^{n+1} y_i P_i(x),$$

where

$$P_i(x) = \frac{V(x_1, \dots, x_{i-1}, x, x_{i+1}, \dots, x_{n+1})}{V(x_1, \dots, x_{n+1})},$$

for i = 1, ..., n + 1 are polynomials of degree n such that

$$P_i(x_j) = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases}$$

### Example

The equation of the line passing through points  $(x_1, y_1), (x_2, y_2)$  is

$$y = y_1 \frac{x_2 - x}{x_2 - x_1} + y_2 \frac{x - x_1}{x_2 - x_1}.$$

### Example

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### Example

The equation of the parabola (or a line) passing through points  $(x_1, y_1), (x_2, y_2), (x_3, y_3)$  is

$$\begin{split} y &= y_1 \frac{(x_3 - x)(x_3 - x_2)(x_2 - x)}{(x_3 - x_1)(x_3 - x_2)(x_2 - x_1)} + y_2 \frac{(x_3 - x_1)(x_3 - x)(x - x_1)}{(x_3 - x_1)(x_3 - x_2)(x_2 - x_1)} + \\ &+ y_3 \frac{(x - x_1)(x - x_2)(x_2 - x_1)}{(x_3 - x_1)(x_3 - x_2)(x_2 - x_1)} = y_1 \frac{(x_3 - x)(x_2 - x)}{(x_3 - x_1)(x_2 - x_1)} + y_2 \frac{(x_3 - x)(x - x_1)}{(x_3 - x_2)(x_2 - x_1)} + \\ &+ y_3 \frac{(x - x_1)(x - x_2)}{(x_3 - x_1)(x_3 - x_2)}. \end{split}$$

#### Remark

The polynomial P(x) is called Lagrange interpolation polynomial.

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## Proposition

If function  $f \in \mathcal{C}^{n+1}([a,b])$  and polynomial P(x) of degree at most n satisfy

$$P(x_i) = f(x_i)$$
 for  $i = 1, \dots, n+1$ 

for pairwise distinct  $x_1, \ldots, x_{n+1} \in [a, b]$  then for any  $x \in [a, b]$  there exists  $\min(x, x_1, \ldots, x_{n+1}) < \xi < \max(x, x_1, \ldots, x_{n+1})$  such that

$$f(x) - P(x) = \frac{f^{(n+1)}(\xi)}{(n+1)!} \prod_{i=1}^{n+1} (x - x_i).$$

## Example

Let  $f(x) = \cos x$ . Then there exists a unique polynomial P(x) of degree at most 11, which attains the same values as the function f(x) at 12 pairwise distinct points  $x_1, \ldots, x_{12} \in [0, \pi]$  and

$$|f(x) - P(x)| \le \frac{\pi^{12}}{12!} < 0.002$$

for any  $x \in [0, \pi]$ .

## Equation of an Affine Hyperplane

### Proposition

Let  $p_1, \ldots, p_n \in \mathbb{R}^n$  be n points, where  $p_1 = (p_{11}, \ldots, p_{1n}), p_2 = (p_{21}, \ldots, p_{2n}), \ldots, p_{n-1} = (p_{n1}, \ldots, p_{nn}).$  An equation of an affine hyperplane passing through  $p_1, \ldots, p_n$  (if it is unique up to a non-zero constant, i.e.,  $p_1, \ldots, p_n$  do not lie on an affine subspace of dimension n-2) is given by the equation

$$\det \begin{bmatrix} x_1 & x_2 & \dots & x_n & 1 \\ p_{11} & p_{12} & \dots & p_{1n} & 1 \\ p_{21} & p_{22} & \dots & p_{2n} & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ p_{(n-1)1} & p_{(n-1)2} & \dots & p_{(n-1)n} & 1 \\ p_{n1} & p_{n2} & \dots & p_{nn} & 1 \end{bmatrix} = 0.$$

## Example

Equation of a line passing through points  $(a_1,b_1),(a_2,b_2)\in\mathbb{R}^2$  is equal to

$$\det \begin{bmatrix} x_1 & x_2 & 1 \\ a_1 & b_1 & 1 \\ a_2 & b_2 & 1 \end{bmatrix} = 0,$$

that is, by the Laplace expansion along the first row,

$$(b_1-b_2)x_1-(a_1-a_2)x_2+a_1b_2-a_2b_1=0.$$

For example, the line passing through (1,2),(2,5) has equation

$$\det \begin{bmatrix} x_1 & x_2 & 1 \\ 1 & 2 & 1 \\ 2 & 5 & 1 \end{bmatrix} = 0,$$

i.e.,

$$-3x_1 + x_2 + 1 = 0.$$

### Hoffman-Wieland Theorem

### Proposition

Let  $A, B \in M(n \times n; \mathbb{R})$  be two symmetric matrices, i.e.  $A = A^{\mathsf{T}}, B = B^{\mathsf{T}}$ . Let  $\lambda_1(A) \leqslant \lambda_2(A) \leqslant \ldots \lambda_n(A)$  and  $\lambda_1(B) \leqslant \lambda_2(B) \leqslant \ldots \lambda_n(B)$  be all eigenvalues of A and B. Then

$$\sum_{i=1}^n (\lambda_i(A) - \lambda_i(B))^2 \leqslant \|A - B\|_F^2.$$

#### Proof.

Let  $A = QD_AQ^{\mathsf{T}}$  and  $B = PD_BP^{\mathsf{T}}$  be spectral decompositions of A and B, respectively, where  $D_A, D_B$  are diagonal matrices with weakly increasing elements along the main diagonal. Then

$$\begin{split} &\sum_{i=1}^{n} \left(\lambda_i(A) - \lambda_i(B)\right)^2 = \mathsf{Tr}\left((D_A - D_B)^2\right) = \\ &= \mathsf{Tr}\left(D_A^2\right) - 2\,\mathsf{Tr}(D_A D_B) + \mathsf{Tr}\left(D_B^2\right). \end{split}$$

### Hoffman-Wielandt Theorem

#### Proof.

Moreover

$$\|A - B\|_F^2 = \operatorname{Tr}((A - B)^2) = \operatorname{Tr}((QD_AQ^{\mathsf{T}} - PD_BP^{\mathsf{T}})^2) =$$

$$\operatorname{Tr}(D_A^2) - 2\operatorname{Tr}(QD_AQ^{\mathsf{T}}PD_BP^{\mathsf{T}}) + \operatorname{Tr}(D_B^2).$$

Let  $U = [u_{ij}] = Q^{\mathsf{T}}P$  be an orthogonal matrix. Then the inequality is equivalent to

$$\operatorname{Tr}(U^{\mathsf{T}}D_AUD_B)\leqslant \operatorname{Tr}(D_AD_B),$$

or equivalently

$$\sum_{i,j=1}^n \lambda_i(A)\lambda_j(B)u_{ij}^2 \leqslant \sum_{i=1}^n \lambda_i(A)\lambda_i(B).$$

# Hoffman-Wielandt Theorem (continued)

Proof.

$$\sum_{i,j=1}^n \lambda_i(A)\lambda_j(B)u_{ij}^2 \leqslant \sum_{i=1}^n \lambda_i(A)\lambda_i(B).$$

The left-hand side is a linear function in the entries of a doubly-stochastic matrix, and, it assumes a maximum at a vertex of the polyhedron of doubly-stochastic matrices, which, by the Birkhoff-von Neumann, is a matrix of some permutation  $\sigma \in S_n$ . The theorem follows by the rearrangement inequality.

# Hoffman-Wielandt Theorem (continued)

#### Remark

The inequality becomes an equation when it is possible to diagonalize A and B simultaneously keeping the order of eigenvalues.

#### Remark

Similar inequality holds for any complex matrices and its eigenvalues.

# Rearrangement Inequality

### Proposition

For any real numbers

$$x_1 \leqslant x_2 \leqslant \ldots \leqslant x_n,$$
  
 $v_1 \leqslant v_2 \leqslant \ldots \leqslant v_n,$ 

and any permutation  $\sigma \in S_n$ 

$$x_1y_n + x_2y_{n-1} + \dots + x_ny_1 \le$$
  
 $\le x_1y_{\sigma(1)} + x_2y_{\sigma(2)} + \dots + x_ny_{\sigma(n)} \le$   
 $\le x_1y_1 + x_2y_2 + \dots + x_ny_n.$ 

### Proof.

(sketch, by induction) If  $x_1 \geqslant x_2$  and  $y_1 \geqslant y_2$  then

$$(x_1-x_2)(y_1-y_2) \geqslant 0$$
,

$$x_1y_1 + x_2y_2 \geqslant x_1y_2 + x_2y_1$$
.

## Rearrangement Inequality

#### Proof.

Let  $\sigma$  be a permutation maximizing the product and assume there exists i such that  $\sigma(i)=j\neq i$  and choose the biggest such i. Then there exists k< i such that  $\sigma(k)=i$ . Consider the terms

$$x_i y_{\sigma(i)} = x_i y_j$$
, and  $x_k y_{\sigma(k)} = x_k y_i$ .

Since j < i we have that

$$x_k \geqslant x_i$$
 and  $y_j \geqslant y_i$ .

If  $x_k=x_i$  or  $y_j=y_i$  then modifying the permutation  $\sigma$  such that  $\sigma'(i)=i$  and  $\sigma'(k)=j$  and  $\sigma'(m)=\sigma(m)$  otherwise does not change the sum. Assume that

$$x_k > x_i$$
 and  $y_i > y_i$ .

But then

$$\sum_{i} x_{i} y_{\sigma'(i)} > \sum_{i} x_{i} y_{\sigma(i)}.$$



### Minimax Theorems

### Proposition

Let  $M \in M(n \times n; \mathbb{C})$  be any Hermitian matrix with real eigenvalues

$$\lambda_1 \geqslant \lambda_2 \geqslant \ldots \geqslant \lambda_n$$
,

and an orthogonal basis of  $\mathbb{C}^n$ 

$$\mathcal{B}=(v_1,\ldots,v_n),$$

such that

$$M\mathbf{v}_j = \lambda_j \mathbf{v}_j,$$

for  $j = 1, \ldots, j$ . Then

$$\min_{\substack{v \in V, v \neq 0 \\ \dim V = k}} R(M,v) \leqslant \lambda_k \leqslant \max_{\substack{v \in V, v \neq 0 \\ \dim V = n-k+1}} R(M,v)$$

The inequalities are sharp (for the upper bound take for example  $V = lin(v_k, ..., v_n)$  and  $v = v_k$ ).



# Minimax Theorems (continued)

### Proof.

Let  $V \subset \mathbb{C}^n$  be a subspace such that dim V = n - k + 1. By the dimension count there exists  $w \neq 0$  such that  $\|w\| = 1$  and

$$w \in V \cap \operatorname{lin}(v_1, \ldots, v_k).$$

Assume

$$w = \sum_{j=1}^k \alpha_j v_j.$$

Then

$$\max_{\substack{v \in V, v \neq 0 \\ \dim V = n-k+1}} R(M, v) \geqslant R(M, w) = \sum_{j=1}^{\kappa} \lambda_j |\alpha_j|^2 \geqslant \lambda_k \sum_{j=1}^{\kappa} |\alpha_j|^2 = \lambda_k.$$

Obviously  $R(M, v_k) = \lambda_k$ .

# Minimax Theorems (continued)

#### Proof.

The second inequality follows in a similar manner by considering (exercise)

$$w \in V \cap \text{lin}(v_k, \ldots, v_n).$$



# Minimax Theorems (continued)

#### Proof.

The second inequality follows in a similar manner by considering (exercise)

$$w \in V \cap \operatorname{lin}(v_k, \ldots, v_n).$$

#### Remark

The same proof works for a real symmetric matrix  $A \in M(n \times n; \mathbb{R})$ .

### Courant-Fischer Theorem

### Corollary

Let  $M \in M(n \times n; \mathbb{C})$  be any Hermitian matrix with real eigenvalues

$$\lambda_1 \geqslant \lambda_2 \geqslant \ldots \geqslant \lambda_n$$
.

Then

$$\max_{\dim V=k} \min_{v \in V, v \neq 0} R(M,v) = \lambda_k = \min_{\dim V=n-k+1} \max_{v \in V, v \neq 0} R(M,v).$$