

MA 110

Linear Algebra and Differential Equations

Lecture 10

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Axiomatic approach to the determinant function

For an [axiomatic approach to the determinant function](#), we refer to the write up on the Moodle page of the course. This is meant as optional reading for those interested and will have no bearing on any of the exams in this course.

In this approach, the three [crucial properties](#) of the determinant function mentioned earlier become the [defining properties](#). Suppose we write $n \times n$ matrices in terms of their columns. A real-valued function defined on the set of all $n \times n$ matrices satisfying the three crucial properties is called a **determinant function**. We then show that such a function exists and is unique. The formulas for the expansion of a determinant in terms of the j th row or the k th column can then be deduced.

Linear Transformations

Just as we can define a continuous function from a subset of \mathbb{R}^n to \mathbb{R}^m , we now define a 'linear' function from a subspace of $\mathbb{R}^{n \times 1}$ to $\mathbb{R}^{m \times 1}$.

Let V be a subspace of $\mathbb{R}^{n \times 1}$, and let W be a subspace of $\mathbb{R}^{m \times 1}$. A **linear transformation** or a **linear map** from V to W is a function $T : V \rightarrow W$ which 'preserves' the operations of addition and scalar multiplication, that is, for all $\mathbf{x}, \mathbf{y} \in V$ and $\alpha \in \mathbb{R}$,

$$T(\mathbf{x} + \mathbf{y}) = T(\mathbf{x}) + T(\mathbf{y}) \quad \text{and} \quad T(\alpha \mathbf{x}) = \alpha T(\mathbf{x}).$$

It follows that if $T : V \rightarrow W$ is linear, then $T(\mathbf{0}) = \mathbf{0}$, and T 'preserves' linear combinations of vectors in V , that is,

$$T(\alpha_1 \mathbf{x}_1 + \cdots + \alpha_k \mathbf{x}_k) = \alpha_1 T(\mathbf{x}_1) + \cdots + \alpha_k T(\mathbf{x}_k)$$

for all $\mathbf{x}_1, \dots, \mathbf{x}_k \in V$ and $\alpha_1, \dots, \alpha_k \in \mathbb{R}$.

Model Example

Let $V := \mathbb{R}^{n \times 1}$, $W := \mathbb{R}^{m \times 1}$ and \mathbf{A} be an $m \times n$ matrix, that is, $\mathbf{A} \in \mathbb{R}^{m \times n}$. Define $T_{\mathbf{A}} : \mathbb{R}^{n \times 1} \rightarrow \mathbb{R}^{m \times 1}$ by

$$T_{\mathbf{A}}(\mathbf{x}) = \mathbf{A}\mathbf{x} \quad \text{for } \mathbf{x} \in V.$$

The properties of matrix multiplication show that $T_{\mathbf{A}}$ is linear.

Conversely, suppose $T : \mathbb{R}^{n \times 1} \rightarrow \mathbb{R}^{m \times 1}$ is linear. We show that $T = T_{\mathbf{A}}$ for some $\mathbf{A} \in \mathbb{R}^{m \times n}$. Let $\mathbf{x} := [x_1 \ \cdots \ x_n]^T \in \mathbb{R}^{n \times 1}$. Then $\mathbf{x} = x_1 \mathbf{e}_1 + \cdots + x_n \mathbf{e}_n$, where $\mathbf{e}_1, \dots, \mathbf{e}_n$ are the basic column vectors in $\mathbb{R}^{n \times 1}$. Since T is linear, we obtain

$$T(\mathbf{x}) = x_1 T(\mathbf{e}_1) + \cdots + x_n T(\mathbf{e}_n).$$

Define $\mathbf{c}_k := T(\mathbf{e}_k)$ for $k = 1, \dots, n$, and $\mathbf{A} := [\mathbf{c}_1 \ \cdots \ \mathbf{c}_n]$. Then $T(\mathbf{x}) = x_1 \mathbf{c}_1 + \cdots + x_n \mathbf{c}_n = \mathbf{A}\mathbf{x}$ for all $\mathbf{x} \in \mathbb{R}^{n \times 1}$. Thus $\mathbf{A} \in \mathbb{R}^{m \times n}$ and $T = T_{\mathbf{A}}$. (Note: k th column of \mathbf{A} is $T(\mathbf{e}_k)$.)

Thus every linear transformation $T : \mathbb{R}^{n \times 1} \rightarrow \mathbb{R}^{m \times 1}$ is given by

$$T \left(\begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \right) := \begin{bmatrix} a_{11}x_1 + \cdots + a_{1n}x_n \\ \vdots \\ a_{m1}x_1 + \cdots + a_{mn}x_n \end{bmatrix} \quad \text{for} \quad \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \in \mathbb{R}^{n \times 1},$$

where $a_{11}, \dots, a_{1n}, \dots, a_{m1}, \dots, a_{mn} \in \mathbb{R}$.

Similarly, one can define a linear map $T : \mathbb{R}^{1 \times n} \rightarrow \mathbb{R}^{1 \times m}$, and find that for $\begin{bmatrix} x_1 & \cdots & x_n \end{bmatrix} \in \mathbb{R}^{1 \times n}$,

$$T \left(\begin{bmatrix} x_1 & \cdots & x_n \end{bmatrix} \right) := \begin{bmatrix} a_{11}x_1 + \cdots + a_{1n}x_n & \cdots & a_{m1}x_1 + \cdots + a_{mn}x_n \end{bmatrix}.$$

Remark: Let D be an open subset of $\mathbb{R}^{1 \times 2}$, $[x_0, y_0] \in D$, and let a function $f : D \rightarrow \mathbb{R}$ be differentiable at $[x_0, y_0]$. Then the **total derivative** of f at $[x_0, y_0]$ is a linear map (which depends on f) given by $T([x, y]) = \alpha x + \beta y$ for $[x, y] \in \mathbb{R}^{1 \times 2}$, where $\alpha := f_x(x_0, y_0)$ and $\beta := f_y(x_0, y_0)$.

Let $\mathbf{A}, \mathbf{B} \in \mathbb{R}^{m \times n}$ and $\alpha, \beta \in \mathbb{R}$. Then $\alpha\mathbf{A} + \beta\mathbf{B} \in \mathbb{R}^{m \times n}$ and

$$T_{\alpha\mathbf{A}+\beta\mathbf{B}}(\mathbf{x}) = (\alpha\mathbf{A} + \beta\mathbf{B})\mathbf{x} = \alpha T_{\mathbf{A}}(\mathbf{x}) + \beta T_{\mathbf{B}}(\mathbf{x})$$

for $\mathbf{x} \in \mathbb{R}^{n \times 1}$. We write this as follows:

$$T_{\alpha\mathbf{A}+\beta\mathbf{B}} = \alpha T_{\mathbf{A}} + \beta T_{\mathbf{B}}.$$

Next, let $\mathbf{A} \in \mathbb{R}^{m \times n}$ and $\mathbf{B} \in \mathbb{R}^{n \times p}$. Then $\mathbf{AB} \in \mathbb{R}^{m \times p}$, and

$$T_{\mathbf{AB}}(\mathbf{x}) = (\mathbf{AB})\mathbf{x} = \mathbf{A}(\mathbf{B}\mathbf{x}) = T_{\mathbf{A}}(\mathbf{B}\mathbf{x}) = T_{\mathbf{A}}(T_{\mathbf{B}}(\mathbf{x})) = T_{\mathbf{A} \circ T_{\mathbf{B}}}(\mathbf{x})$$

for $\mathbf{x} \in \mathbb{R}^{p \times 1}$ by the associativity of matrix multiplication. Thus

$$T_{\mathbf{AB}} = T_{\mathbf{A}} \circ T_{\mathbf{B}}.$$

This says that the linear map associated with the product \mathbf{AB} of matrices \mathbf{A} and \mathbf{B} is the composition of the linear maps associated with \mathbf{A} and associated with \mathbf{B} in the same order. This partially justifies the [definition of matrix multiplication](#).

Examples

Let $\mathbf{A} \in \mathbb{R}^{2 \times 2}$. Then $T_{\mathbf{A}} : \mathbb{R}^{2 \times 1} \rightarrow \mathbb{R}^{2 \times 1}$.

(i) Let $\mathbf{A} := \begin{bmatrix} 2 & 0 \\ 0 & 2 \end{bmatrix}$. Then $T_{\mathbf{A}} : \begin{bmatrix} x_1 & x_2 \end{bmatrix}^T \mapsto \begin{bmatrix} 2x_1 & 2x_2 \end{bmatrix}^T$.

$T_{\mathbf{A}}$ stretches each vector by a factor of 2.

(ii) Let $\mathbf{A} := \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$. Then $T_{\mathbf{A}} : \begin{bmatrix} x_1 & x_2 \end{bmatrix}^T \mapsto \begin{bmatrix} x_2 & x_1 \end{bmatrix}^T$.

$T_{\mathbf{A}}$ is the reflection in the line $x_1 = x_2$.

(iii) Let $\mathbf{A} := \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix}$. Then $T_{\mathbf{A}} : \begin{bmatrix} x_1 & x_2 \end{bmatrix}^T \mapsto \begin{bmatrix} -x_1 & -x_2 \end{bmatrix}^T$.

$T_{\mathbf{A}}$ is the reflection in the origin.

(iv) Let $\mathbf{A} := \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}$, where $\theta \in (-\pi, \pi]$. Then

$$T_{\mathbf{A}} : \begin{bmatrix} x_1 & x_2 \end{bmatrix}^T \mapsto \begin{bmatrix} x_1 \cos \theta - x_2 \sin \theta & x_1 \sin \theta + x_2 \cos \theta \end{bmatrix}^T.$$

$T_{\mathbf{A}}$ is the rotation through an angle θ .

These are [geometric interpretations](#) of matrices.

While constructing an $m \times n$ matrix which represents a transformation from $\mathbb{R}^{n \times 1}$ to $\mathbb{R}^{m \times 1}$, we made an explicit use of the standard basis of $\mathbb{R}^{n \times 1}$ consisting of the basic column vectors $\mathbf{e}_1, \dots, \mathbf{e}_n$ (in this order). Also, we implicitly used the standard basic column vectors $\mathbf{e}_1, \dots, \mathbf{e}_m$ in $\mathbb{R}^{m \times 1}$ (in this order) when we wrote $\mathbf{A} := [T(\mathbf{e}_1) \ \cdots \ T(\mathbf{e}_n)]$.

More generally, let an ordered basis $E := (\mathbf{x}_1, \dots, \mathbf{x}_n)$ of $\mathbb{R}^{n \times 1}$ and an ordered basis $F := (\mathbf{y}_1, \dots, \mathbf{y}_m)$ of $\mathbb{R}^{m \times 1}$ be given. Then there are unique $a_{11}, \dots, a_{1n}, \dots, a_{m1}, \dots, a_{mn} \in \mathbb{R}$ such that

$$\begin{aligned} T(\mathbf{x}_1) &= a_{11}\mathbf{y}_1 + \cdots + a_{j1}\mathbf{y}_j + \cdots + a_{m1}\mathbf{y}_m, \\ &\quad \vdots \qquad \qquad \qquad \vdots \qquad \qquad \qquad \vdots \\ T(\mathbf{x}_k) &= a_{1k}\mathbf{y}_1 + \cdots + a_{jk}\mathbf{y}_j + \cdots + a_{mk}\mathbf{y}_m, \\ &\quad \vdots \qquad \qquad \qquad \vdots \qquad \qquad \qquad \vdots \\ T(\mathbf{x}_n) &= a_{1n}\mathbf{y}_1 + \cdots + a_{jn}\mathbf{y}_j + \cdots + a_{mn}\mathbf{y}_m. \end{aligned}$$

The $m \times n$ matrix $[a_{jk}]$ is called the **matrix of the linear transformation** $T : \mathbb{R}^{n \times 1} \rightarrow \mathbb{R}^{m \times 1}$ with respect to the ordered basis $E := (\mathbf{x}_1, \dots, \mathbf{x}_n)$ of $\mathbb{R}^{n \times 1}$ and the ordered basis $F := (\mathbf{y}_1, \dots, \mathbf{y}_m)$ of $\mathbb{R}^{m \times 1}$. This matrix is denoted by $\mathbf{M}_F^E(T)$.

Note: The k th column of $\mathbf{M}_F^E(T)$ is $[a_{1k} \ \cdots \ a_{mk}]^T$, where $T(\mathbf{x}_k) = a_{1k}\mathbf{y}_1 + \cdots + a_{jk}\mathbf{y}_j + \cdots + a_{mk}\mathbf{y}_m$ for $k = 1, \dots, n$.

The $m \times n$ matrix $\mathbf{M}_F^E(T)$ represents the linear map T in the following sense. For $\alpha_1, \dots, \alpha_n \in \mathbb{R}$,

$$\begin{aligned} T(\alpha_1 \mathbf{x}_1 + \cdots + \alpha_n \mathbf{x}_n) &= \sum_{k=1}^n \alpha_k T(\mathbf{x}_k) = \sum_{k=1}^n \alpha_k \left(\sum_{j=1}^m a_{jk} \mathbf{y}_j \right) \\ &= \sum_{j=1}^m \left(\sum_{k=1}^n a_{jk} \alpha_k \right) \mathbf{y}_j = \beta_1 \mathbf{y}_1 + \cdots + \beta_m \mathbf{y}_m, \end{aligned}$$

where $\beta_j := \sum_{k=1}^n a_{jk} \alpha_k$ for $j = 1, \dots, m$. Thus

$$T\left(\begin{bmatrix} \mathbf{x}_1 & \cdots & \mathbf{x}_n \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix}\right) = \begin{bmatrix} \mathbf{y}_1 & \cdots & \mathbf{y}_m \end{bmatrix} \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_m \end{bmatrix},$$

$$\text{while } \mathbf{M}_F^E(T) \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \vdots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_m \end{bmatrix}.$$

Conversely, suppose we are given an $m \times n$ matrix \mathbf{A} . Define $T : \mathbb{R}^{n \times 1} \rightarrow \mathbb{R}^{m \times 1}$ as follows. For $\mathbf{x} := \alpha_1 \mathbf{x}_1 + \cdots + \alpha_n \mathbf{x}_n$, let

$$T(\mathbf{x}) := \beta_1 \mathbf{y}_1 + \cdots + \beta_m \mathbf{y}_m, \quad \text{where } \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_m \end{bmatrix} := \mathbf{A} \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix}.$$

Then T is a linear map, and $\mathbf{M}_F^E(T) = \mathbf{A}$.

In particular, this holds if E and F are the standard ordered bases of $\mathbb{R}^{n \times 1}$ and $\mathbb{R}^{m \times 1}$ respectively.

Examples

(i) Consider the map $T : \mathbb{R}^{2 \times 1} \rightarrow \mathbb{R}^{3 \times 1}$ defined by

$$T(\mathbf{x}) := \begin{bmatrix} x_1 - x_2 & -x_1 + 2x_2 & x_2 \end{bmatrix}^T \text{ for } \mathbf{x} := \begin{bmatrix} x_1 & x_2 \end{bmatrix}^T.$$

Then T is a linear map. If $E := (\mathbf{e}_1, \mathbf{e}_2)$ is the standard ordered basis for $\mathbb{R}^{2 \times 1}$ and $F := (\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3)$ is the standard

ordered basis for $\mathbb{R}^{3 \times 1}$, then $\mathbf{M}_F^E(T) = \begin{bmatrix} 1 & -1 \\ -1 & 2 \\ 0 & 1 \end{bmatrix}$.

On the other hand, let $E' := (\mathbf{e}'_1, \mathbf{e}'_2)$, where $\mathbf{e}'_1 := \mathbf{e}_1$ and $\mathbf{e}'_2 := \mathbf{e}_1 + \mathbf{e}_2$, and let $F' := (\mathbf{e}'_1, \mathbf{e}'_2, \mathbf{e}'_3)$, where $\mathbf{e}'_1 := \mathbf{e}_1$, $\mathbf{e}'_2 := \mathbf{e}_1 + \mathbf{e}_2$ and $\mathbf{e}'_3 := \mathbf{e}_1 + \mathbf{e}_2 + \mathbf{e}_3$. Then

$$T(\mathbf{e}'_1) = \begin{bmatrix} 1 & -1 & 0 \end{bmatrix}^T = 2 \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}^T - \begin{bmatrix} 1 & 1 & 0 \end{bmatrix}^T = 2\mathbf{e}'_1 - \mathbf{e}'_2,$$

$$T(\mathbf{e}'_2) = \begin{bmatrix} 0 & 1 & 1 \end{bmatrix}^T = - \begin{bmatrix} 1 & 0 & 0 \end{bmatrix}^T + \begin{bmatrix} 1 & 1 & 1 \end{bmatrix}^T = -\mathbf{e}'_1 + \mathbf{e}'_3.$$

$$\text{Hence } \mathbf{M}_{F'}^{E'}(T) = \begin{bmatrix} 2 & -1 \\ -1 & 0 \\ 0 & 1 \end{bmatrix}.$$

(ii) Consider the map $T : \mathbb{R}^{3 \times 1} \rightarrow \mathbb{R}^{3 \times 1}$ defined by $T(\mathbf{x}) := \begin{bmatrix} 2.9x_1 + 0.6x_2 - 0.1x_3 & 2.9x_1 + 1.6x_2 - 1.1x_3 & 2.5x_1 + x_2 + 1.5x_3 \end{bmatrix}^T$ for $\mathbf{x} := \begin{bmatrix} x_1 & x_2 & x_3 \end{bmatrix}^T$. Then T is a linear map.

If $E := (\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3)$ is the standard ordered basis for $\mathbb{R}^{3 \times 1}$, then

$$\mathbf{M}_E^E(T) = \frac{1}{10} \begin{bmatrix} 29 & 6 & -1 \\ 29 & 16 & -11 \\ 25 & 10 & 15 \end{bmatrix}.$$

On the other hand, let $E' := (\mathbf{e}'_1, \mathbf{e}'_2, \mathbf{e}'_3)$, where

$$\mathbf{e}'_1 := \begin{bmatrix} -1 & 3 & -1 \end{bmatrix}^T, \mathbf{e}'_2 := \begin{bmatrix} 1 & -1 & 3 \end{bmatrix}^T, \mathbf{e}'_3 := \begin{bmatrix} 2 & 1 & 4 \end{bmatrix}^T.$$

Then it can be checked that

$$T(\mathbf{e}'_1) = \mathbf{e}'_1, \quad T(\mathbf{e}'_2) = 2\mathbf{e}'_2, \quad T(\mathbf{e}'_3) = 3\mathbf{e}'_3.$$

$$\text{Hence } \mathbf{M}_{E'}^{E'}(T) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix}, \text{ which is a diagonal matrix!}$$

Remark: We have shown that if $T : \mathbb{R}^{n \times 1} \rightarrow \mathbb{R}^{m \times 1}$ is linear map, and if E and F are ordered bases of $\mathbb{R}^{n \times 1}$ and $\mathbb{R}^{m \times 1}$ respectively, then T is represented by an $m \times n$ matrix $\mathbf{M}_F^E(T)$ with respect to E and F . Now let V and W be subspaces of dimension n and m of some possibly higher dimensional spaces of vectors, and let T be a linear map from V to W . Even in this case, if E and F are ordered bases of V and W respectively, then the linear map T from V to W is represented, with respect to E and F , by an $m \times n$ matrix. This matrix is denoted by $\mathbf{M}_F^E(T)$.

Thus if $E := (\mathbf{x}_1, \dots, \mathbf{x}_n)$ and $F := (\mathbf{y}_1, \dots, \mathbf{y}_m)$, and we let $\mathbf{A} := \mathbf{M}_F^E(T)$, then for $\mathbf{x} = \alpha_1 \mathbf{x}_1 + \dots + \alpha_n \mathbf{x}_n \in V$ and $\mathbf{y} = \beta_1 \mathbf{y}_1 + \dots + \beta_m \mathbf{y}_m \in W$, we see that

$$T(\mathbf{x}) = \mathbf{y} \iff \mathbf{A} \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} \beta_1 \\ \vdots \\ \beta_m \end{bmatrix}.$$

Remark: Let V be a subspace of $\mathbb{R}^{n \times 1}$, W be a subspace of $\mathbb{R}^{m \times 1}$, and let $T : V \rightarrow W$ be a linear map. Two important subspaces associated with T are as follows.

(i) $\mathcal{N}(T) := \{\mathbf{x} \in V : T(\mathbf{x}) = \mathbf{0}\}$, called the **null space** of T ,

(ii) $\mathcal{I}(T) := \{T(\mathbf{x}) : \mathbf{x} \in V\}$, called the **image space** of T .

We note that

a linear map T is one-one $\iff \mathcal{N}(T) = \{\mathbf{0}\}$, and

a linear map T is onto $\iff \mathcal{I}(T) = W$.

Further, if $V := \mathbb{R}^{n \times 1}$, $W := \mathbb{R}^{m \times 1}$, and $\mathbf{A} \in \mathbb{R}^{m \times n}$, then

$$\mathcal{N}(T_{\mathbf{A}}) = \{\mathbf{x} \in \mathbb{R}^{n \times 1} : \mathbf{A}\mathbf{x} = \mathbf{0}\} = \mathcal{N}(\mathbf{A}),$$

$$\mathcal{I}(T_{\mathbf{A}}) = \{\mathbf{A}\mathbf{x} : \mathbf{x} \in \mathbb{R}^{n \times 1}\} = \mathcal{C}(\mathbf{A}).$$

The last equality follows by noting that if $\mathbf{A} = [\mathbf{c}_1 \ \cdots \ \mathbf{c}_n]$, then $\mathbf{A}\mathbf{x} = x_1\mathbf{c}_1 + \cdots + x_n\mathbf{c}_n$ for $\mathbf{x} := [x_1 \ \cdots \ x_n] \in \mathbb{R}^{n \times 1}$.

Example

Let $\mathbf{A} := \begin{bmatrix} 1 & -1 \\ -1 & 2 \\ 0 & 1 \end{bmatrix} \in \mathbb{R}^{3 \times 2}$. Then $T_{\mathbf{A}} : \mathbb{R}^{2 \times 1} \rightarrow \mathbb{R}^{3 \times 1}$.

In fact, $T_{\mathbf{A}} : \begin{bmatrix} x_1 & x_2 \end{bmatrix}^T \mapsto \begin{bmatrix} x_1 - x_2 & -x_1 + 2x_2 & x_2 \end{bmatrix}^T$ for all $\begin{bmatrix} x_1 & x_2 \end{bmatrix}^T \in \mathbb{R}^{2 \times 1}$. Clearly, $\mathcal{N}(T_{\mathbf{A}}) = \{\mathbf{0}\}$. Also,

$$\mathcal{I}(T_{\mathbf{A}}) = \left\{ \begin{bmatrix} y_1 & y_2 & y_3 \end{bmatrix}^T \in \mathbb{R}^{3 \times 1} : y_1 + y_2 - y_3 = 0 \right\}.$$

To see this, note that $(x_1 - x_2) + (-x_1 + 2x_2) - x_2 = 0$ for all $\begin{bmatrix} x_1 & x_2 \end{bmatrix}^T \in \mathbb{R}^{2 \times 1}$, and if $\begin{bmatrix} y_1 & y_2 & y_3 \end{bmatrix}^T \in \mathbb{R}^{3 \times 1}$ satisfies $y_1 + y_2 - y_3 = 0$, then we may let $x_1 := y_1 + y_3$, $x_2 := y_3$, so that $x_1 - x_2 = y_1$, $-x_1 + 2x_2 = y_2$ and $x_2 = y_3$, that is, $T_{\mathbf{A}}(\begin{bmatrix} x_1 & x_2 \end{bmatrix}^T) = \begin{bmatrix} y_1 & y_2 & y_3 \end{bmatrix}^T$.

Note: $\mathcal{I}(T_{\mathbf{A}})$ is a plane through the origin $\begin{bmatrix} 0 & 0 & 0 \end{bmatrix}^T$ in $\mathbb{R}^{3 \times 1}$.

Complex Numbers

In our development of matrix theory, we have so far used real numbers as scalars, and we have considered matrices whose entries are real numbers. Now we introduce an extension of \mathbb{R} which has all the properties that \mathbb{R} has (and one more).

A **complex number** is a 2×2 matrix $\begin{bmatrix} a & b \\ -b & a \end{bmatrix}$, where $a, b \in \mathbb{R}$. The set of all complex numbers is denoted by \mathbb{C} . Addition and multiplication in \mathbb{C} are defined as in $\mathbb{R}^{2 \times 2}$. Thus

$$\begin{bmatrix} a & b \\ -b & a \end{bmatrix} + \begin{bmatrix} c & d \\ -d & c \end{bmatrix} = \begin{bmatrix} a+c & b+d \\ -(b+d) & a+c \end{bmatrix}$$

and

$$\begin{bmatrix} a & b \\ -b & a \end{bmatrix} \begin{bmatrix} c & d \\ -d & c \end{bmatrix} = \begin{bmatrix} ac-bd & ad+bc \\ -(ad+bc) & ac-bd \end{bmatrix}.$$

These algebraic operations possess all the usual properties such as associativity, distributivity and commutativity.

Moreover, the map $a \mapsto \begin{bmatrix} a & 0 \\ 0 & a \end{bmatrix}$ from \mathbb{R} to \mathbb{C} is one-one.

Hence we identify $a \in \mathbb{R}$ with $\begin{bmatrix} a & 0 \\ 0 & a \end{bmatrix} \in \mathbb{C}$. We define

$$i := \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}, \quad \text{so that } i^2 = \begin{bmatrix} -1 & 0 \\ 0 & -1 \end{bmatrix} = -\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

We write $\begin{bmatrix} a & b \\ -b & a \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} a + \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix} b \in \mathbb{C}$ as $a + ib$.

It follows that $(a + ib) + (c + id) = (a + c) + i(b + d)$ and $(a + ib)(c + id) = (ac - bd) + i(ad + bc)$.

Let $z \in \mathbb{C}$. Then $z = x + iy$ for unique $x, y \in \mathbb{R}$. Then x is called the **real part** of z , and it is denoted by $\Re(z)$, while y is called the **imaginary part** of z , and it is denoted by $\Im(z)$.

The complex number $x - iy$ is called the **conjugate** of $z = x + iy$, and it is denoted by \bar{z} .