Chapter 6: Linear Transformations

- Let A be an $m \times n$ matrix with real entries.
- 2 Then A defines a function

$$T_A: \mathbb{R}^n \longrightarrow \mathbb{R}^m, \quad T_A(v) = Av.$$

② By properties of matrix multiplication, T_A satisfies the following properties for all $c \in \mathbb{R}$ and $v, w \in \mathbb{R}^n$.

$$T_A(v+w) = A(v+w) = Av + Aw = T_A(v) + T_A(w)$$
$$T_A(cv) = cT_A(v).$$

- **1** We say that T_A respects the two operations in the vector space \mathbb{R}^n .
- In this chapter we study such maps between vector spaces.
- **Openition.** Let V, W be vector spaces over \mathbb{F} . A linear transformation $T: V \longrightarrow W$ is a function satisfying

$$T(v+w) = T(v) + T(w)$$
 and $T(cv) = cT(v)$

where $v, w \in V$ and $c \in \mathbb{F}$.

• If $T: V \to W$ is a linear transformation, then T(0) = 0.

Examples of Linear Transformations

- **●** Examples: If vector spaces V, W are vector spaces over \mathbb{F} , the "zero map" $T_0: V \to W$ defined as $T_0(v) = 0$ for all $v \in V$, is clearly a linear transformation.
- **②** The **identity map** $I: V \to V$ defined as I(v) = v for all $v \in V$, is clearly a linear map.
- **3** Let $c \in \mathbb{R}, V = W = \mathbb{R}^2$. Define $T : \mathbb{R}^2 \longrightarrow \mathbb{R}^2$ by

$$T\left[\begin{array}{c} x \\ y \end{array}\right] = \left[\begin{array}{cc} c & 0 \\ 0 & c \end{array}\right] \left[\begin{array}{c} x \\ y \end{array}\right] = \left[\begin{array}{c} cx \\ cy \end{array}\right] = c \left[\begin{array}{c} x \\ y \end{array}\right].$$

T is a linear transformation since for all $v, w \in \mathbb{R}^2$ and $d \in \mathbb{R}$,

$$T(v + w) = c(v + w) = cv + cw = T(v) + T(w)$$

 $T(dv) = c(dv) = d(cv) = dT(v),$

9 Rotation: Fix θ and define $T: \mathbb{R}^2 \longrightarrow \mathbb{R}^2$ by

$$T\left(\left[\begin{array}{c} x \\ y \end{array}\right]\right) = \left[\begin{array}{cc} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{array}\right] \left[\begin{array}{c} x \\ y \end{array}\right] = \left[\begin{array}{c} x\cos\theta - y\sin\theta \\ x\sin\theta + y\cos\theta \end{array}\right].$$

- Then $T(e_1) = (\cos \theta, \sin \theta)^{\mathsf{t}}$ and $T(e_2) = (-\sin \theta, \cos \theta)^{\mathsf{t}}$.
- **\odot** Hence T rotates every vector by an angle θ in anticlockwise direction.

Linear Transformations: Examples

• Differentiation. Let \mathcal{D} be the vector space of differentiable functions $f: \mathbb{R} \longrightarrow \mathbb{R}$ such that $f^{(n)}$ exists for all n. Define $D: \mathcal{D} \longrightarrow \mathcal{D}$ by

$$D(f) = f^{'}.$$

② Then D is a linear transformation since for all $a, b \in \mathbb{R}$ and $f, g \in \mathcal{D}$,

$$D(af + bg) = af' + bg' = aD(f) + bD(g).$$

1 Integration. Let V be the vector space of all continuous functions $f: \mathbb{R} \to \mathbb{R}$. Define $\mathcal{I}: V \longrightarrow V$ by

$$\mathcal{I}(f)(x) = \int_0^x f(t) \, dt.$$

- \bullet By properties of integration, \mathcal{I} is a linear transformation.
- **1** The map $T: \mathbb{R} \to \mathbb{R}$ given by $T(x) = x^2$ is not linear.
- Let $V = M_{n \times n}(\mathbb{F})$ be the vector space of all $n \times n$ matrices over \mathbb{F} . Fix $A \in V$. The map $T : V \to V$ given by T(N) = AN is linear.

The null space and image of a linear transformation

- Let $T: V \to W$ be a linear transformation of vector spaces.
- 2 There are two important subspaces associated with T.
 - Nullspace of $T = \mathcal{N}(T) = \{v \in V \mid T(v) = 0\}.$
 - Image of $T = \operatorname{Im}(T) = \{T(v) \mid v \in V\}.$
- **3** Let V be a finite dimensional vector space. Suppose that α, β are scalars. If $v, w \in \mathcal{N}(T)$ then $T(\alpha v + \beta w) = \alpha T(v) + \beta T(w) = 0$. Hence $\alpha v + \beta w \in \mathcal{N}(T)$. Therefore $\mathcal{N}(T)$ is a subspace of V.
- The dimension of $\mathcal{N}(T)$ denoted as nullity (T), is called the nullity of T.
- **5** Suppose that $v, w \in V$. Then

$$\alpha T(v) + \beta T(w) = T(\alpha v + \beta w) \in \text{Im}(T).$$

- **6** Hence $\operatorname{Im}(T)$ is a subspace of W.
- The dimension of $\operatorname{Im}(T)$, denoted by $\operatorname{rank}(T)$, is called the rank of T.
- § If A is an $m \times n$ matrix and $T_A : \mathbb{R}^n \to \mathbb{R}^m$ is the map $T_A(u) = Au$, Then $\operatorname{Im} T = \mathcal{C}(A)$. Thus $\operatorname{rank}(T) = \operatorname{rank} A = \dim \mathcal{C}(A)$.
- The nullspace of T_A is the null space of A. Hence nullity T_A = null

Construction of linear transformations

- **Proposition.** Let $T: V \to W$ be a linear map of vector spaces. Then T is 1-1 if and only if $\mathcal{N}(T) = \{0\}$.
- **Definition.** A 1-1 and onto linear transformation $T:V\to W$ of vector spaces V and W over the same field of scalars is called an **isomorphism**. In this case, we write $V\simeq W$ and say that V and W are isomorphic.
- **Proposition.** Let V, W be vector spaces over \mathbb{F} . Assume V is finite dimensional with $\{v_1, \ldots, v_n\}$ as a basis. Let (w_1, \ldots, w_n) be an arbitrary sequence of vectors in W. Then there is a unique linear map $T: V \to W$ with $T(v_i) = w_i$, for all $i = 1, \ldots, n$.
- **Proof**: (Uniqueness) For any $v \in V$, write $v = a_1v_1 + \cdots + a_nv_n$, for scalars a_i . Then $T(v) = a_1T(v_1) + \cdots + a_nT(v_n) = a_1w_1 + \cdots + a_nw_n$. So T is determined by (w_1, \ldots, w_n) .
- **(Existence)** Given $v \in V$ write (uniquely) $v = a_1v_1 + \cdots + a_nv_n$, for scalars a_i and then define $T(v) = a_1w_1 + \cdots + a_nw_n$.
- \bigcirc Show that T is linear.

Linear Transformations: Rank and Nullity

The rank-nullity Theorem. Let $T: V \to W$ be a linear transformation of vector spaces where V is finite dimensional. Then

$$rank(T) + nullity(T) = \dim V.$$

- **2** Proof: Suppose dim V = n. Let $B = \{v_1, v_2, \dots, v_k\}$ be a basis of $\mathcal{N}(T)$.
- **3** Now extend B to a basis $C = \{v_1, v_2, \dots, v_k, w_1, w_2, \dots, w_{n-k}\}$ of V.
- lacksquare Now show that a basis of $\mathrm{Im}\,(T)$ is

$$D = \{T(w_1), T(w_2), \dots, T(w_{n-k})\}.$$

6 Note that any $v \in V$ can be expressed uniquely as

$$v = \alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_k v_k + \beta_1 w_1 + \dots + \beta_{n-k} w_{n-k}.$$

• This implies that

$$T(v) = \alpha_1 T(v_1) + \dots + \alpha_k T(v_k) + \beta_1 T(w_1) + \dots + \beta_{n-k} T(w_{n-k})$$

= $\beta_1 T(w_1) + \dots + \beta_{n-k} T(w_{n-k}).$

 \bullet Hence Im T = L(D).

Proof of the Rank-Nullity Theorem

• Now show that D is linearly independent. Suppose there are scalars $\beta_1, \ldots, \beta_{n-k}$ such that

$$\beta_1 T(w_1) + \dots + \beta_{n-k} T(w_{n-k}) = T(\beta_1 w_1 + \dots + \beta_{n-k} w_{n-k}) = 0.$$

2 Then $\beta_1 w_1 + \cdots + \beta_{n-k} w_{n-k} \in \mathcal{N}(T)$. Therefore there are scalars $\alpha_1, \alpha_2, \ldots, \alpha_k$ such that

$$\beta_1 w_1 + \beta_2 w_2 + \dots + \beta_{n-k} w_{n-k} = \alpha_1 v_1 + \alpha_2 v_2 + \dots + \alpha_k v_k$$
$$\implies \beta_1 = \beta_2 = \dots = \beta_{n-k} = 0.$$

 \bullet Hence D is a basis of Im T. Thus

$$rank(T) = n - k = \dim V - \dim \mathcal{N}(T).$$

- ① Therefore $rank(T) + nullity(T) = \dim V$.
- **Orollary.** If there exists an isomorphism $T: V \to W$ of finite dimensional vector spaces V, W then dim $V = \dim W$.
- **Proof.** If T is an isomorphism then T is 1-1. Hence nullity (T)=0. Since T is onto $\operatorname{rank} T=\dim W$. Hence

$$rankT = rankT + nullity T = \dim V = \dim W.$$

Sum of two subspaces and its dimension

Definition. Let V, W be subspaces of a vector space U. Then the sum of V and W, denoted V + W, is the subspace

$$V + W = \{x + y \mid x \in V, y \in W\}.$$

- **Theorem.** Let V, W be subspaces of a finite dimensional vector space U. Then $\dim(V+W) = \dim V + \dim W \dim(V\cap W).$
- **O** Proof: We shall give a sketch of a proof leaving you to fill in the details.
- Consider the set $V \times W = \{(v, w) : v \in V, w \in W\}$. This set is a vector space with component-wise addition and scalar multiplication.
- **o** Check that the dimension of this space is $\dim V + \dim W$.
- **o** Define a linear map $T: V \times W \to V + W$ by T((v, w)) = v w.
- **②** Check that T is onto and that the nullspace of T is $\{(v,v):v\in V\cap W\}$.
- The result now follows from the rank nullity theorem for linear maps.

Coordinate vectors with respect to a basis

- Let V be a finite dimensional vector space of dimension n over \mathbb{F} .
- ② By an ordered basis of V we mean a sequence v_1, v_2, \ldots, v_n of distinct vectors of V such that the set $B = \{v_1, \ldots, v_n\}$ is linearly independent.
- **1** Let $u \in V$. Then there are uniquely determined $a_1, a_2, \ldots, a_n \in \mathbb{F}$ so that

$$u = a_1 v_1 + a_2 v_2 + \dots + a_n v_n, \ a_i \in \mathbb{F}.$$

lacktriangle Define the coordinate vector of u with respect to the ordered basis B by

$$[u]_B = \begin{bmatrix} a_1 & a_2 & \cdots & a_n \end{bmatrix}^t$$
.

10 Note that for vectors $u, v \in V$ and scalar $a \in \mathbb{F}$, we have

$$[u+v]_B = [u]_B + [v]_B, [av]_B = a[v]_B.$$

- **1** Therefore the map $T: V \to \mathbb{F}^n$ defined as $T(v) = [v]_B$ is a linear map.
- **Theorem.** Let V be a vector space over \mathbb{F} and dim V = n. Then $T: V \to \mathbb{F}^n$ given by $T(v) = [v]_B$ is an isomorphism.
- **Proof.** Let $v = a_1v_1 + a_2v_2 + \cdots + a_nv_n$. T is clearly onto. Let $T(v) = a_1[v_1]_B + a_2[v_2]_B + \cdots + a_n[v_n]_B = (a_1, a_2, \dots, a_n) = 0$. Hence each $a_i = 0$. Thus v = 0. Hence $n = \dim V = \operatorname{rank} T = \dim \mathbb{F}^n = n$.

- Let V and W be finite dimensional vector spaces with dim V = n and dim W = m. Suppose $E = (v_1, v_2, \ldots, v_n)$ is an ordered basis for V and $F = (w_1, w_2, \ldots, w_m)$ is an ordered basis for W.
- 2 Let $T: V \longrightarrow W$ be a linear transformation.
- We define $M_F^E(T)$, the matrix of T with respect to the ordered bases E and F, to be the $m \times n$ matrix whose jth column is $[T(v_j)]_F$:

$$M_F^E(T) = [[T(v_1)]_F [T(v_2)]_F \cdots [T(v_n)]_F].$$

- **Example:** Let A be an $m \times n$ matrix over \mathbb{F} and consider the linear map $T_A : \mathbb{F}^n \to \mathbb{F}^m$ given by $T_A(v) = Av$, for $v \in \mathbb{F}^n$
- Consider the the standard bases $E = (e_1, \ldots, e_n)$ of \mathbb{F}^n and $F = (e_1, \ldots, e_m)$ of \mathbb{F}^n . Then

$$M_F^E(T_A) = [[Ae_1]_F, [Ae_2]_F, \dots, [Ae_n]_F] = A.$$

- Let $\mathcal{L}(V, W)$ denote the set of all linear transformations from V to W. Suppose $S, T \in \mathcal{L}(V, W)$ and c is a scalar.
- **2** For any $x \in V$, define

$$(S+T)(x) = S(x) + T(x)$$
$$(cS)(x) = cS(x)$$

- **3** It is easy to show that $\mathcal{L}(V, W)$ is a vector space under these operations.
- **Proposition.** Fix ordered bases E and F of V and W respectively. For all $S, T \in \mathcal{L}(V, W)$ and scalars c we have

$$M_F^E(S+T) = M_F^E(S) + M_F^E(T)$$
 (1)

$$M_E^E(cS) = cM_E^E(S) \tag{2}$$

$$M_F^E(S) = M_F^E(T) \iff S = T.$$
 (3)

- **9** Proof: We shall prove only (3). Let $E = \{u_1, u_2, \ldots, u_n\}$ be an ordered basis of V and $F = \{v_1, v_2, \ldots, v_m\}$ be an ordered basis of W. Then $M_F^E(S) = [[S(u_1)]_F, \ldots, [S(u_n)]_F]$ $M_F^E(T) = [[T(u_1)]_F, \ldots, [T(u_n)]_F]$.

Proposition. Suppose V, W are vector spaces of dimensions n, m respectively. Suppose $T: V \longrightarrow W$ is a linear transformation. Let $E = (v_1, \ldots, v_n), F = (w_1, \ldots, w_m)$ be ordered bases of V, W resp. Then

$$[T(v)]_F = M_F^E(T)[v]_E, \quad v \in V.$$

- **2** Proof: Let $v = a_1v_1 + a_2v_2 + \cdots + a_nv_n$. Then $[v]_E = (a_1, a_2, \cdots, a_n)^t$.
- Therefore

$$T(v) = a_1 T(v_1) + a_2 T(v_2) + \dots + a_n T(v_n).$$

We have

$$[T(v)]_F = [a_1T(v_1) + \dots + a_nT(v_n)]_F$$

$$= a_1[T(v_1)]_F + \dots + a_n[T(v_n)]_F$$

$$= [[T(v_1)]_F [T(v_2)]_F \dots [T(v_n)]_F] (a_1, a_2, \dots, a_n)^t$$

$$= M_F^E(T)[v]_E.$$

Proposition. Suppose U, V, W are vector spaces of dimension n, p, m respectively. Suppose $T: U \longrightarrow V$ and $S: V \longrightarrow W$ are linear transformations. Suppose E, F, G are ordered bases of U, V, W resp. Then

$$M_G^E(S \circ T) = M_G^F(S)M_F^E(T).$$

● Proof: Let $E = (u_1, u_2, ..., u_n)$. Then, the jth column of $M_G^E(S \circ T)$ is $= [(S \circ T)(u_j)]_G = [S(T(u_j))]_G.$

 ${\color{red} \bullet}$ Now the $j{\rm th}$ column of $M_G^F(S)M_F^E(T)$ is

$$= M_G^F(S)(j\text{th column of } M_F^E(T))$$

$$= M_G^F(S)[T(u_j)]_F$$

$$= [S(T(u_j))]_G \text{ (since } [S(v)]_G = M_G^F(S)[v]_F.$$

- Let $B = (v_1, v_2, \ldots, v_n)$ and $C = (u_1, \ldots, u_n)$ are ordered bases of V.
- **Question.** Given $u \in V$, what is the relation between $[u]_B$ and $[u]_C$?
- **3** Define $M_B^C(I)$, the transition matrix from C to B, to be the $n \times n$ matrix of the identity map $I: (V, C) \to (V, B)$.

$$M_B^C(I) = [[u_1]_B [u_2]_B \cdots [u_n]_B].$$

 \bullet Hence for all $u \in V$, we have

$$[u]_B = M_B^C(I)([u]_C).$$

Proposition. Let V be a finite dimensional vector space and B and C be two ordered bases of V. Then

$$M_B^C(I) = (M_C^B(I))^{-1}.$$

9 Proof: Consider the sequence of identity maps

$$(V,C) \xrightarrow{I} (V,B) \xrightarrow{I} (V,C).$$

 $\bullet \text{ Then } M_B^C(I)M_C^B(I) = M_C^C(I) = I \implies M_B^C(I) = M_C^B(I)^{-1}.$

• Example: Let $V = \mathbb{R}^3$ and let

$$v_{1} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \ v_{2} = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}, \ v_{3} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, \ u_{1} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \ u_{2} = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \ u_{3} = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

② Consider the ordered bases $B = (v_1, v_2, v_3)$ and $C = (u_1, u_2, u_3)$. Thus

$$M = M^{(I)} = \begin{bmatrix} 1 & 0 & 0 \\ -1 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix}.$$

Matrix of a linear operator under change of bases

- Let V be a finite dimensional vector space. A linear map $T: V \to V$ is said to be a linear operator on V. Let B, C be ordered bases of V.
- ② The matrix $M_B^B(T)$ is the matrix of T with respect to the ordered basis B.
- **3** Recall that the transition matrix $M_B^C(I)$ from C to B is the matrix of the identity map $I:(V,C)\to (V,B)$, and $M_B^C(I)=M_C^B(I)^{-1}$.
- **1 Theorem.** Let V be a finite dimensional vector space and B, C be two bases of V. Then

$$M_B^B(T) = (M_C^B(I))^{-1} M_C^C(T) M_C^B(I).$$

• Proof: Consider the sequence of linear operators where the bases used for computation of matrices of the linear transformations are specified:

$$(V,B) \xrightarrow{I} (V,C) \xrightarrow{T} (V,C) \xrightarrow{I} (V,B).$$

 \bullet Since $T=I\circ T\circ I,\, M_B^B(T)=M_B^C(I)M_C^C(T)M_C^B(I).$ Therefore

$$M_B^B(T) = (M_C^B(I))^{-1} M_C^C(T) M_C^B(I).$$

Example: Consider the linear transformation

$$T: \mathbb{R}^2 \to \mathbb{R}^2, \ T(e_1) = e_1, \ T(e_2) = e_1 + e_2.$$

② Let $C = (e_1, e_2)$ and $B = (e_1 + e_2, e_1 - e_2)$ are ordered bases of \mathbb{R}^2 .

$$M_C^C(T) = \left[\begin{array}{cc} 1 & 1 \\ 0 & 1 \end{array} \right], \ \ M_C^B(I) = \left[\begin{array}{cc} 1 & 1 \\ 1 & -1 \end{array} \right], \ \ M_B^C(I) = \left[\begin{array}{cc} 1/2 & 1/2 \\ 1/2 & -1/2 \end{array} \right].$$

$$M_B^B(T) \ = \ \left[\begin{array}{cc} 1/2 & 1/2 \\ 1/2 & -1/2 \end{array} \right] \left[\begin{array}{cc} 1 & 1 \\ 0 & 1 \end{array} \right] \left[\begin{array}{cc} 1 & 1 \\ 1 & -1 \end{array} \right] = \frac{1}{2} \left[\begin{array}{cc} 3 & -1 \\ 1 & 1 \end{array} \right].$$

- **●** Example: Let M be the $(n+1) \times (n+1)$ matrix, with rows and columns indexed by $\{0, 1, ..., n\}$, and with entry in row i and column j, $0 \le i, j \le n$, given by $\binom{j}{i}$.
- lacktriangle We show that M is invertible and find the inverse explicitly.
- **3** Consider the vector space $\mathcal{P}_n(\mathbb{R})$ of real polynomials of degree $\leq n$.
- **1** Then $B = (1, x, x^2, \dots, x^n)$ and $C = (1, x 1, (x 1)^2, \dots, (x 1)^n)$ are both ordered bases of $\mathcal{P}_n(\mathbb{R})$.
- We find the change of basis matrix $M = M_C^B(I)$. For $0 \le j \le n$ we have

$$x^{j} = (1 + (x - 1))^{j}$$

$$= \sum_{i=0}^{j} {j \choose i} (x - 1)^{i}$$

$$= \sum_{i=0}^{n} {j \choose i} (x - 1)^{i},$$

• where in the last step we have used the fact that $\binom{j}{i} = 0$ for i > j.

- Thus $M = \begin{bmatrix} \binom{j}{i} \end{bmatrix} = M_C^B(I)$ and hence it is invertible.
- **②** To find the inverse of M, use the fact that $M^{-1} = (M_C^B)^{-1} = M_R^C(I)$.
- § For $0 \le j \le n$, use the Binomial Theorem:

$$(x-1)^{j} = \sum_{i=0}^{j} (-1)^{j-i} {j \choose i} x^{i}$$
$$= \sum_{i=0}^{n} (-1)^{j-i} {j \choose i} x^{i}.$$

• Thus the entry in row i and column j of M^{-1} is $(-1)^{j-i} {j \choose i}$. Therefore

$$\left[\begin{pmatrix} j \\ i \end{pmatrix} \right]^{-1} = \left[(-1)^{j-i} \begin{pmatrix} j \\ i \end{pmatrix} \right].$$