

Lecture 14 - Linear Transformations and Matrix Multiplication

October 28, 2022

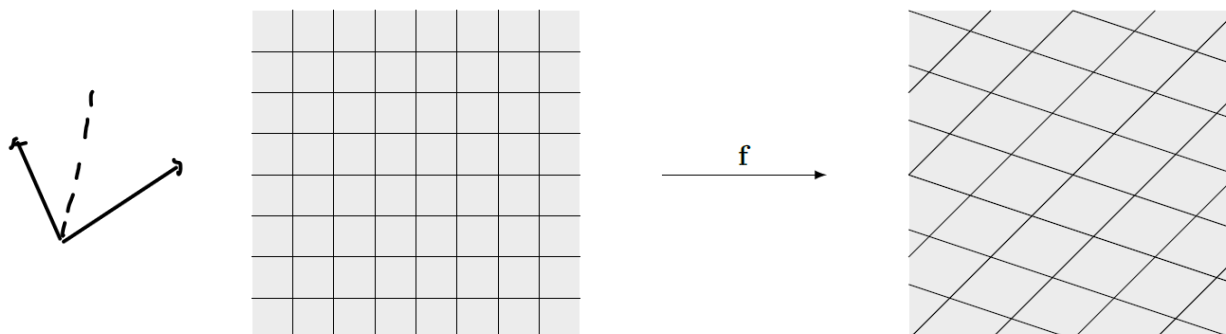
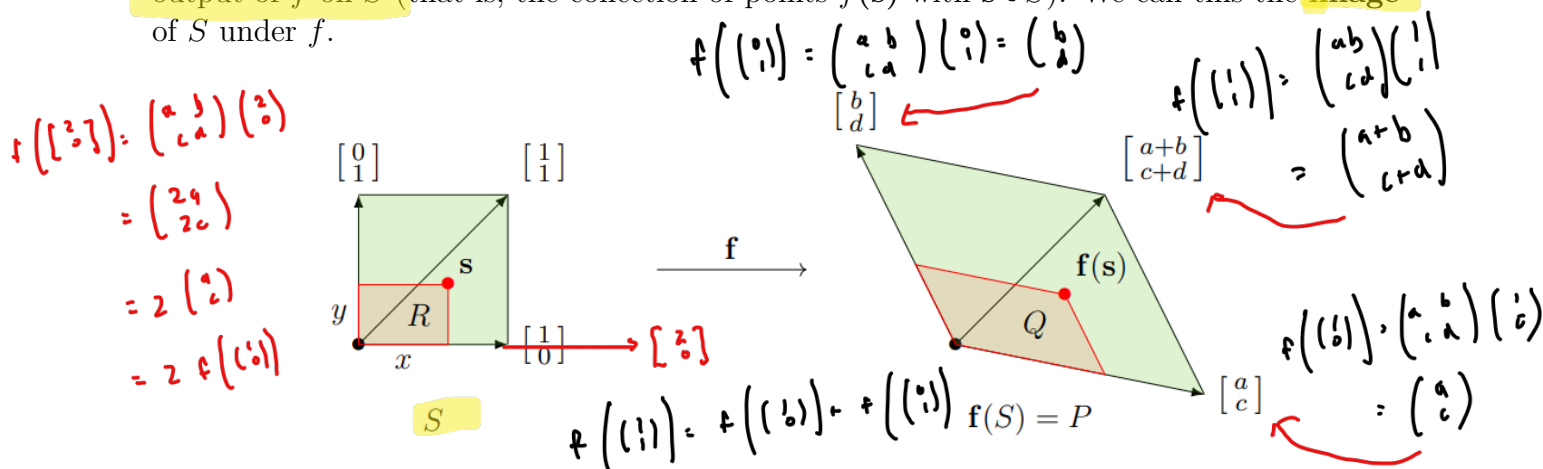
Goals: Characterize a linear function in terms of its interaction with vector addition and scalar multiplication, compute rotation matrices, and compose linear functions using matrix multiplication.

Recall the definition of linear and affine functions (in matrix form):

Definition: A function $f : \mathbb{R}^n \rightarrow \mathbb{R}^m$ is called

- a **linear function or linear transformation** if there is an $m \times n$ matrix A such that $f(\mathbf{x}) = A\mathbf{x}$ (recall that the j th column of A is $f(\mathbf{e}_j)$).
- an **affine function or affine transformation** if there is an $m \times n$ matrix A such that $f(\mathbf{x}) = A\mathbf{x} + \mathbf{b}$.

Let us visualize the effect of the linear transformation $f : \mathbb{R}^2 \rightarrow \mathbb{R}^2$ with associated matrix $A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$, where the columns are not multiples of each other. Let S denote the unit square $\{(x, y) : 0 \leq x, y \leq 1\}$. We can think of \mathbb{R}^2 as being tiled by copies of S . Let $f(S)$ denote the output of f on S (that is, the collection of points $f(\mathbf{s})$ with $\mathbf{s} \in S$). We call this the **image** of S under f .



works for all,
not just
standard
bases

- **Linearity Principle:** for $c_1, c_2 \in \mathbb{R}$ and $\mathbf{v}_1, \mathbf{v}_2 \in \mathbb{R}^2$, we have
 $f(c_1 \mathbf{v}_1 + c_2 \mathbf{v}_2) = c_1 f(\mathbf{v}_1) + c_2 f(\mathbf{v}_2)$. *works w/ vec addition & scalar mult*
- **Tiling Principle:** f transforms the tiling of \mathbb{R}^2 by copies of S into the tiling of \mathbb{R}^2 by copies of $f(S)$.

It turns that we can characterize linear functions based on their interaction with the vector operations.

Theorem 14.2.1: A function $g: \mathbb{R}^n \rightarrow \mathbb{R}^m$ is **linear precisely** when it respects the vector operations

- $g(c\mathbf{x}) = cg(\mathbf{x})$ *scalar multiplication*
- $g(\mathbf{x} + \mathbf{y}) = g(\mathbf{x}) + g(\mathbf{y})$ *vector addition*

$$f(c_1 \vec{v}_1 + c_2 \vec{v}_2) = A(c_1 \vec{v}_1 + c_2 \vec{v}_2)$$

for all scalars $c \in \mathbb{R}$ and vectors $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$.

★ If $g: \mathbb{R}^n \rightarrow \mathbb{R}^m$ and $h: \mathbb{R}^p \rightarrow \mathbb{R}^n$ are linear, then so is the **composition** $g \circ h: \mathbb{R}^p \rightarrow \mathbb{R}^m$.

Example 1: For any **non-zero linear subspace** V of \mathbb{R}^n , the projection function

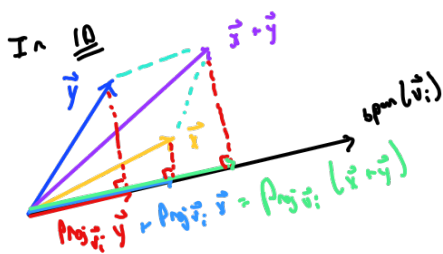
$\text{Proj}_V: \mathbb{R}^n \rightarrow \mathbb{R}^n$ is **linear** (We actually discussed this in the case where V is one dimensional in Lecture 6).

One dimensional: $\text{Proj}_{\vec{v}} \{c_1 \vec{v}_1 + \dots + c_k \vec{v}_k\} = c_1 \text{Proj}_{\vec{v}} \vec{x}_1 + c_2 \text{Proj}_{\vec{v}} \vec{x}_2 + \dots + c_k \text{Proj}_{\vec{v}} \vec{x}_k$

Let $\{\vec{v}_1, \dots, \vec{v}_k\}$ be an orthogonal basis of V . By orthogonal projection theorem, $\text{Proj}_V \vec{v} = \text{Proj}_{\vec{v}_1} \vec{v} + \dots + \text{Proj}_{\vec{v}_k} \vec{v}$

Algebraic

$$\begin{aligned} \text{Proj}_{\vec{v}_i} (\vec{x} + \vec{y}) &= \frac{\vec{v}_i \cdot (\vec{x} + \vec{y})}{\vec{v}_i \cdot \vec{v}_i} \vec{v}_i = \frac{\vec{v}_i \cdot \vec{x}}{\vec{v}_i \cdot \vec{v}_i} \vec{v}_i + \frac{\vec{v}_i \cdot \vec{y}}{\vec{v}_i \cdot \vec{v}_i} \vec{v}_i \\ &= \text{Proj}_{\vec{v}_i} (\vec{x}) + \text{Proj}_{\vec{v}_i} (\vec{y}) \end{aligned}$$

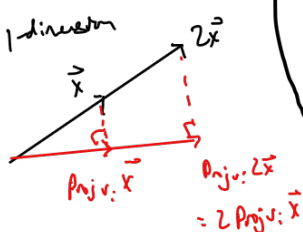


Multiple Dimensions

$$\begin{aligned} \text{Proj}_V (\vec{x} + \vec{y}) &= \text{Proj}_{\vec{v}_1} (\vec{x} + \vec{y}) + \dots + \text{Proj}_{\vec{v}_k} (\vec{x} + \vec{y}) \\ &= \text{Proj}_{\vec{v}_1} (\vec{x}) + \text{Proj}_{\vec{v}_1} (\vec{y}) + \dots + \text{Proj}_{\vec{v}_k} (\vec{x}) + \text{Proj}_{\vec{v}_k} (\vec{y}) \\ &= \text{Proj}_V (\vec{x}) + \text{Proj}_V (\vec{y}) \end{aligned}$$

Therefore projection respects vector addition

In 1-dimensional



$$\text{Proj}_{\vec{v}_i} (c\vec{x}) = \frac{\vec{v}_i \cdot c\vec{x}}{\vec{v}_i \cdot \vec{v}_i} \vec{v}_i = c \left(\frac{\vec{v}_i \cdot \vec{x}}{\vec{v}_i \cdot \vec{v}_i} \vec{v}_i \right) = c \text{Proj}_{\vec{v}_i} \vec{x} \rightarrow \text{Proj}_V (c\vec{x}) = c \text{Proj}_V (\vec{x})$$

Therefore, projection respects scalar multiplication.

Definition: Let A be an $m \times n$ and B an $n \times p$ matrix defined by

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \quad \text{and} \quad B = \begin{bmatrix} b_{11} & b_{12} & \cdots & b_{1p} \\ b_{21} & b_{22} & \cdots & b_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ b_{n1} & b_{n2} & \cdots & b_{np} \end{bmatrix}$$

Let $T_A: \mathbb{R}^n \rightarrow \mathbb{R}^m$ and $T_B: \mathbb{R}^p \rightarrow \mathbb{R}^n$ be the linear transformations defined by $T_A(\mathbf{x}) = A\mathbf{x}$ and $T_B(\mathbf{y}) = B\mathbf{y}$. Then the composition $T_A \circ T_B: \mathbb{R}^p \rightarrow \mathbb{R}^m$ is a linear transformation, and the associated matrix is AB which we call the **matrix product** of A and B .

Theorem 14.3.2: The entries of AB are the dot products of rows of A with columns of B . If we write

a_i is row, treated as row $A = \begin{bmatrix} \text{--- } \mathbf{a}_1 \text{ ---} \\ \text{--- } \mathbf{a}_2 \text{ ---} \\ \vdots \\ \text{--- } \mathbf{a}_m \text{ ---} \end{bmatrix}, \quad B = \begin{bmatrix} | & | & \cdots & | \\ \mathbf{b}_1 & \mathbf{b}_2 & \cdots & \mathbf{b}_p \\ | & | & \cdots & | \end{bmatrix},$ *b_j is col, treated as col*

then we have

$$AB = \begin{bmatrix} \mathbf{a}_1 \cdot \mathbf{b}_1 & \mathbf{a}_1 \cdot \mathbf{b}_2 & \cdots & \mathbf{a}_1 \cdot \mathbf{b}_p \\ \mathbf{a}_2 \cdot \mathbf{b}_1 & \mathbf{a}_2 \cdot \mathbf{b}_2 & \cdots & \mathbf{a}_2 \cdot \mathbf{b}_p \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{a}_m \cdot \mathbf{b}_1 & \mathbf{a}_m \cdot \mathbf{b}_2 & \cdots & \mathbf{a}_m \cdot \mathbf{b}_p \end{bmatrix} = \begin{bmatrix} | & | & \cdots & | \\ A\mathbf{b}_1 & A\mathbf{b}_2 & \cdots & A\mathbf{b}_p \\ | & | & \cdots & | \end{bmatrix}.$$

More explicitly, the ij -entry of AB is

i th row of A $\sum_{k=1}^n a_{ik} b_{kj},$ *j th col of B*

the dot product of \mathbf{a}_i and \mathbf{b}_j .

Example 2: Let $A = \begin{bmatrix} 2 & 5 \\ 1 & 1 \end{bmatrix}$ and $B = \begin{bmatrix} 3 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix}$. Compute AB . Can you compute BA ?

$$AB = \begin{bmatrix} 2 & 5 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 3 & 1 & 0 \\ 0 & -1 & 1 \end{bmatrix} = \begin{bmatrix} 6 & -3 & 5 \\ 3 & 0 & 1 \end{bmatrix}$$

2x2 *2x3* *2x3*

You can't compute BA because it's a 2×3 times 2×2 . Matrix mult is not commutative.

Diagonal matrix is only diag is nonzero

Let $C = \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix}$. Compute $C^2 = CC$. What is C^n for any positive integer n ?

$$C^2 = \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 2^2 & 0 \\ 0 & 1^2 \end{bmatrix}$$

$$C^n = \begin{bmatrix} 2^n & 0 \\ 0 & 1^n \end{bmatrix}$$

$$C^3 = \begin{bmatrix} 4 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 8 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 2^3 & 0 \\ 0 & 1^3 \end{bmatrix}$$

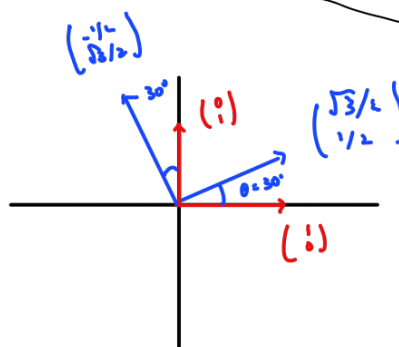
Example 3: Consider the matrix $A = \begin{bmatrix} \frac{\sqrt{3}}{2} & -\frac{1}{2} \\ \frac{1}{2} & \frac{\sqrt{3}}{2} \end{bmatrix}$. What does A do geometrically?

Test it on standard basis:

$$A \begin{pmatrix} 1 \\ 0 \end{pmatrix} = \begin{pmatrix} \sqrt{3}/2 \\ 1/2 \end{pmatrix}$$

$$A \begin{pmatrix} 0 \\ 1 \end{pmatrix} = \begin{pmatrix} -1/2 \\ \sqrt{3}/2 \end{pmatrix}$$

A rotates \mathbb{R}^2 by 30°
counterclockwise



$$A = \begin{bmatrix} \cos(30^\circ) & -\sin(30^\circ) \\ \sin(30^\circ) & \cos(30^\circ) \end{bmatrix}$$

In general, the matrix of counterclockwise rotation of \mathbb{R}^2 around the origin by θ is

$$A_\theta = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}.$$

Note that rotations about the origin in \mathbb{R}^2 commute: $A_\theta A_\phi = A_\phi A_\theta$.

In \mathbb{R}^3 , we will focus on rotations around the x -, y -, and z -axes. We have:

- Rotation about the z -axis counterclockwise by angle θ :

keeps z
constant,
rotate x & y

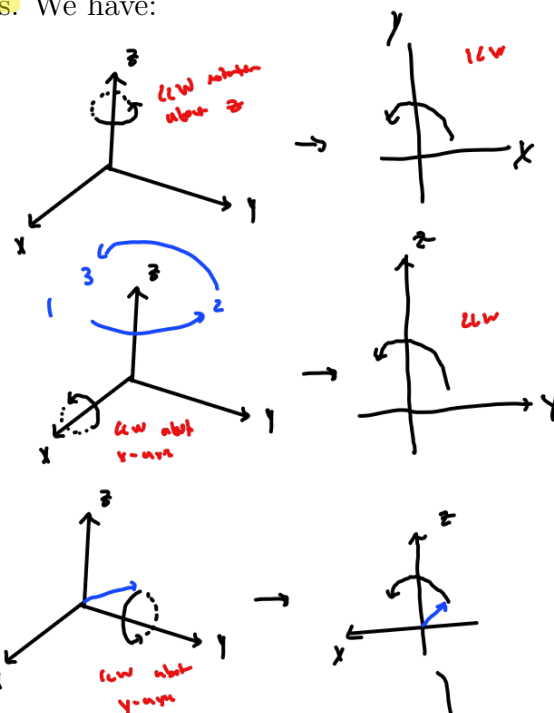
$$R_z(\theta) = \begin{bmatrix} \cos \theta & -\sin \theta & 0 \\ \sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} \dots \\ \dots \\ z \end{pmatrix}$$

- Rotation about the x -axis counterclockwise by angle θ :

$$R_x(\theta) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \theta & -\sin \theta \\ 0 & \sin \theta & \cos \theta \end{bmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix} = \begin{pmatrix} x \\ \dots \\ \dots \end{pmatrix}$$

- Rotation about the y -axis counterclockwise by angle θ :

$$R_y(\theta) = \begin{bmatrix} \cos \theta & 0 & \sin \theta \\ 0 & 1 & 0 \\ -\sin \theta & 0 & \cos \theta \end{bmatrix}$$



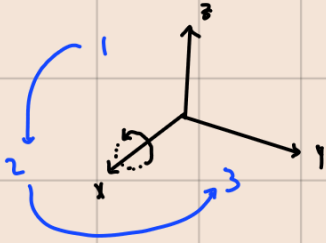
Important: Rotations in \mathbb{R}^3 , in general, **do not commute**.

Algebraically, for example, $R_x(90^\circ)R_y(90^\circ) \neq R_y(90^\circ)R_x(90^\circ)$. Check this by doing the actual matrix multiplication.





z 90 degrees then x 90 degrees



x 90 degrees then z 90 degrees