# 05 Review of Linear Algebra and Transformations 

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## Overview

- n -dimensional vectors
- Dot (Scalar) product
- Bases and Frames
- Homogeneous Coordinates
- 2D and 3D Geometric Transformations


## Vectors

Notation:

$$
\mathbf{x} \in \mathbb{R}^{n}, \quad \mathbf{x}=\left(\begin{array}{c}
x_{1} \\
x_{2} \\
\vdots \\
x_{n}
\end{array}\right), \quad \mathbf{x}=\left(x_{1}, x_{2}, \ldots, x_{n}\right)^{\top}
$$

Length:

$$
\|\mathbf{x}\|=\sqrt{x_{1}^{2}+x_{2}^{2}+\cdots x_{n}^{2}}=\sqrt{\sum_{i=1}^{n} x_{i}^{2}}
$$

Geometric Meanings:
$\square$ An origin $+n$ pairwise perpendicular vectors $\rightarrow$ defines a frame or a coordinate system
$\square$ For a fixed frame, a point $\rightarrow$ a $n$-dimensional vector


## Dot Product

Dot Product of two vectors:

$$
\begin{aligned}
& \langle\mathbf{x}, \mathbf{y}\rangle \\
& \mathbf{x} \cdot \mathbf{y}=\mathbf{x}^{T} \mathbf{y}=\left[\begin{array}{lll}
x_{1} & \cdots & x_{n}
\end{array}\right]\left[\begin{array}{c}
y_{1} \\
\vdots \\
y_{n}
\end{array}\right]
\end{aligned}
$$

Geometric Meanings:


- Commutative:

$$
\mathbf{x} \cdot \mathbf{y}=\|\mathbf{x}\|\|\mathbf{y}\| \cos \theta
$$

$$
\mathbf{x} \cdot \mathbf{y}=\mathbf{y} \cdot \mathbf{x}
$$

- Distributive:

$$
(\mathbf{x}+\mathbf{y}) \cdot \mathbf{z}=\mathbf{x} \cdot \mathbf{z}+\mathbf{y} \cdot \mathbf{z}
$$

Properties

- Linearity

$$
\begin{aligned}
(c \mathbf{x}) \cdot \mathbf{y} & =c(\mathbf{x} \cdot \mathbf{y}) \\
\mathbf{x} \cdot(c \mathbf{y}) & =c(\mathbf{x} \cdot \mathbf{y}) \\
\left(c_{1} \mathbf{x}\right) \cdot\left(c_{2} \mathbf{y}\right) & =\left(c_{1} c_{2}\right)(\mathbf{x} \cdot \mathbf{y})
\end{aligned}
$$

- Non-negativity:

$$
\forall \mathbf{x} \neq 0:\langle\mathrm{x}, \mathrm{x}\rangle>0 \quad\langle\mathrm{x}, \mathrm{x}\rangle=0 \Leftrightarrow \mathrm{x}=0
$$

- Orthogonality:

$$
\forall \mathbf{x} \neq 0, \mathbf{y} \neq 0 \quad \mathbf{x} \cdot \mathbf{y}=0 \Leftrightarrow \mathbf{x} \perp \mathbf{y}
$$

## Norms

- Euclidean norm (sometimes called 2-norm):

$$
\|\mathbf{x}\|=\|\mathbf{x}\|_{2}=\sqrt{\mathbf{x} \cdot \mathbf{x}}=\sqrt{x_{1}^{2}+x_{2}^{2}+\cdots+x_{n}^{2}}=\sqrt{\sum_{i=1}^{n} x_{i}^{2}}
$$

- The length of a vector is defined to be its (Euclidean) norm.
- A unit vector is of length 1.
- Non-negativity properties also hold for the norm:

$$
\forall x \neq 0:\|x\|^{2}>0 \quad \quad\|x\|^{2}=0 \Leftrightarrow x=0
$$

## Linear Dependence

- Linear combination of vectors $\mathbf{x}_{1}, \mathbf{x}_{2}, \ldots \mathbf{x}_{n}$

$$
c_{1} \mathbf{x}_{1}+c_{2} \mathbf{x}_{2}+\cdots+c_{n} \mathbf{x}_{n}
$$

- A set of vectors $X=\left\{\mathbf{x}_{1}, \mathbf{x}_{2}, \ldots \mathbf{x}_{\mathrm{n}}\right\}$ are linearly dependent if there exists a vector $\quad \mathbf{x}_{i} \in X$
that is a linear combination of the rest of the vectors.
- $\ln \mathrm{R}^{\mathrm{n}}$
- sets of $n+1$ vectors are always dependent
a there can be at most n linearly independent vectors


## Bases

- A basis is a linearly independent set of vectors that spans the "whole space". ie., we can write every vector in our space as linear combination of vectors in that set.
- Every set of $n$ linearly independent vectors in $R^{n}$ is a basis of $R^{n}$
- A basis is called
- orthogonal, if every basis vector is orthogonal to all other basis vectors
- orthonormal, if additionally all basis vectors have length 1.





## Bases

- Standard basis in $\mathrm{R}^{\mathrm{n}}$ is made up of a set of unit vectors:

$$
\hat{\mathbf{e}}_{1}=\left(\begin{array}{c}
1 \\
0 \\
0 \\
\vdots \\
0
\end{array}\right), \hat{\mathbf{e}}_{2}=\left(\begin{array}{c}
0 \\
1 \\
0 \\
\vdots \\
0
\end{array}\right), \ldots \hat{\mathbf{e}}_{n}=\left(\begin{array}{c}
0 \\
0 \\
0 \\
\vdots \\
1
\end{array}\right)
$$

- We can write a vector in terms of its standard basis:

$$
\left(\begin{array}{c}
4 \\
7 \\
-3
\end{array}\right)=4 \hat{\mathbf{e}}_{1}+7 \hat{\mathbf{e}}_{2}-3 \hat{\mathbf{e}}_{3}
$$

- Observation: -- to find the coefficient for a particular basis vector, we project our vector onto it.

$$
x_{i}=\hat{\mathbf{e}}_{i} \cdot \mathbf{x}
$$

## Change of Bases

- Suppose we have a new basis $\mathbf{B}=\left[\begin{array}{lll}\mathbf{b}_{1} & \cdots & \mathbf{b}_{n}\end{array}\right], \mathbf{b}_{i} \in \mathbb{R}^{m}$ and a vector $\mathbf{x} \in \mathbb{R}^{m}$ that we would like to represent in terms of $\mathbf{B}$


- Compute the new components
- When B is orthonormal
- $\widetilde{\mathbf{X}}$ is a projection of $\mathbf{x}$ onto $\mathbf{b}_{i}$
- Note the use of a dot product


$$
\widetilde{\mathbf{x}}=\mathbf{B}^{-1} \mathbf{x}
$$

Note: B is an orthonormal matrix, whose inverse is its transpose. we have

$$
\widetilde{\mathbf{x}}=\left[\begin{array}{c}
\mathbf{b}_{1}^{T} \mathbf{x} \\
\vdots \\
\mathbf{b}_{n}^{T} \mathbf{x}
\end{array}\right] \quad \begin{aligned}
& \text { inverse is it } \\
& \text { transpose } . \\
& \text { Therefore }, \\
& \text { we have }
\end{aligned}
$$

## Rank of a Matrix

The rank of a matrix is the number of linearly independent rows or columns.
Examples: $\left(\begin{array}{ll}1 & 1 \\ 0 & 1\end{array}\right)$ has rank 2, but $\left(\begin{array}{ll}2 & 1 \\ 4 & 2\end{array}\right)$ only has rank 1.
Equivalent to the dimension of the range of the linear transformation.

A matrix with full rank is called non-singular, otherwise it is singular.

## Cross Product

Consider two vectors $\boldsymbol{a}$ and $\boldsymbol{b}$ in the 3D space
$\square$ the cross product $\boldsymbol{a} \times \boldsymbol{b}$ is a vector perpendicular to both $\boldsymbol{a}$ and $\boldsymbol{b}$, and therefore normal to the plane containing them

$$
\mathbf{a} \times \mathbf{b}=\|\mathbf{a}\|\|\mathbf{b}\| \sin \theta \mathbf{n}
$$

If the two given vectors are parallel or one vector has zero length, then the cross product is zero

$\square$ Anti-commutative : $\boldsymbol{a} \times \boldsymbol{b}=-(\boldsymbol{b} \times \boldsymbol{a})$
$\square$ Geometric meaning:
Magnitude: the area of a parallelogram
Direction: right-hand rule
Example 1: Prove if $\boldsymbol{c}=\boldsymbol{a} \times \boldsymbol{b}$ then $\boldsymbol{a} \cdot \boldsymbol{c}=0$


## Homogeneous Coordinates (2D)

Consider a point $\boldsymbol{x}$ in the 2D plane:
$\square$ Conventional Notation (inhomogeneous coordinates)
A 2D point can be represented by a pair of coordinates $(x, y) \in R^{2}$
A AD point $\leftarrow$ a 2D vector $\boldsymbol{x}=(x, y)^{T}$; the 2D plane $\leftarrow R^{2}$ vector space
$\square$ Homogeneous Notation (homogeneous coordinates)

- $\widetilde{\boldsymbol{x}}=(x, y, 1)^{T}$, referred to as an augmented vector
- 3D vectors $(x, y, w)^{T}$ can be converted to its corresponding augmented vectors $w(x / w, y / w, 1)$ if $w \neq 0$;

In this case, we consider $(x, y, w)^{T}$ and $\left(\frac{x}{w}, \frac{y}{w}, 1\right)^{T}$ to be equivalent
The set of equivalence classes of vectors from 3D space $R^{3}-(0,0,0)^{T}$ forms the projective space $P^{2}$
$\square$ Homogeneous vector representation of a point $\widetilde{\boldsymbol{x}}=\left(x_{1}, x_{2}, x_{3}\right)^{T}$ corresponds to the point with the 2D inhomogeneous coordinates $\left(\frac{x_{1}}{x_{3}}, \frac{x_{2}}{x_{3}}\right)^{T}$

- Example 2:
$\square$ A 2D point $(3,4)$, what is its homogeneous coordinates?
- $\rightarrow(3,4,1)$
$\square$ What about $(6,8,2)$ ?


## Homogeneous Coordinates (cont.)

Motivation of using Homogeneous Coordinates:
$\square$ To consider and represent linear transformations using matrices
$\square$ Simplify a lot of computations
$\square$ A line in the plane: $a x+b y+c=0$, can be put as $(a, b, c)^{T}$ in Homogeneous Notation
$\square$ The correspondence is NOT one-to-one: $k(a, b, c)^{T}, k \neq 0$ represents the same line
$\square$ The set of equivalence classes of vectors in $R^{3}-(0,0,0)^{T}$ forms the projective space $P^{2}$
$\square$ A planar point $x=(x, y)^{T}$ lies on the line $l=(a, b, c)^{T}$ iff $a x+b y+c=0$
$\square$ If we write the point as an augmented vector: $\widetilde{\boldsymbol{x}}=(x, y, 1)^{T}$
$\square \rightarrow$ inner product of vectors: $(x, y, 1)(a, b, c)^{T}=0$, or simply $\tilde{x} \cdot l=0$

## Homogeneous Coordinates for 3D Points

Inhomogensou Coordinates $(x, y, z)^{T} \rightarrow$ homogeneous coordinates $(x, y, z, 1)^{T}$
$\square$ A 3D plane can be represented as $\boldsymbol{m}=(a, b, c, d)^{T}$, because any point $\boldsymbol{x}=(x, y, z)^{T}$ on this plane satisfies:

$$
a x+b y+c z+d=\tilde{\boldsymbol{x}} \cdot \boldsymbol{m}=0
$$

## 2D Transformations



Figure 2.4 Basic set of 2D planar transformations.
$\square$ Basic Transformations: Translations, Rotations, Scaling, Affine, Projective
$\square$ Euclidean Transformation $=$ Rigid Transformation $=$ Translations + Rotations
$\square$ Similarity Transformation $=$ Uniform scaling + Translations + Rotations + Reflection
$\square$ Affine Transformation $=$ Similarity + non-uniform scaling + shear mapping
$\square$ Projective Transformation

## Linear Transformations

- A transformation $T(\boldsymbol{x})=\boldsymbol{y}, \boldsymbol{x} \in R^{n}, \boldsymbol{y} \in R^{m}$, is a linear transformation if it can be represented by a matrix: $\boldsymbol{y}=\boldsymbol{M} \boldsymbol{x}, \boldsymbol{M} \in R^{m} \times R^{N}$, where $M$ is called the transformation matrix
- With homogeneous coordinates, all basic transformations listed in the previous slide can be treated as linear transformations


## Example: 2D Rotation

To rotate the left figure to the right figure (the left bottom corners of both objects remain at the origin)
$=$ To find a transformation $T$ such that $T\left(\boldsymbol{e}_{1}\right)=\boldsymbol{f}_{1}$, $T\left(\boldsymbol{e}_{2}\right)=\boldsymbol{f}_{2}$
$\rightarrow$ We can solve a linear system using elementary
e2 trigonometry:
$\boldsymbol{f}_{1}=\boldsymbol{M e} \boldsymbol{e}_{1} ; \boldsymbol{f}_{2}=\boldsymbol{M} \boldsymbol{e}_{2}$
under the coordinate system of $\left(\boldsymbol{e}_{1}, \boldsymbol{e}_{2}\right)$,

$$
\boldsymbol{f}_{1}=(\cos \theta, \sin \theta)^{T} ; \boldsymbol{f}_{2}=(-\sin \theta, \cos \theta)
$$

$$
\boldsymbol{M}=\left[\begin{array}{cc}
\cos \theta & -\sin \theta \\
\sin \theta & \cos \theta
\end{array}\right]
$$



## Example: Scaling

2D scaling transformation matrix:

$$
\boldsymbol{M}=\left[\begin{array}{ll}
a & 0 \\
0 & b
\end{array}\right]
$$

as

$$
\boldsymbol{M}\left[\begin{array}{l}
x \\
y
\end{array}\right]=\left[\begin{array}{ll}
a & 0 \\
0 & b
\end{array}\right]\left[\begin{array}{l}
x \\
y
\end{array}\right]=\left[\begin{array}{l}
a x \\
b y
\end{array}\right]
$$


where $a$ and $b$ are called the scaling factors along $x$ and $y$ axes.

If $a=b$ : uniform (isotropic) scaling, shape preserved, only size changed
$\square$ If $a=b=1$ : identity transform

- Directly extendible to 3D


## Example: Shear

Starting from the 2D scaling transformation matrix:

$$
\boldsymbol{M}=\left[\begin{array}{ll}
a & 0 \\
0 & b
\end{array}\right]
$$

Let one of the off-diagonal element be non-zero:

$$
\begin{aligned}
& {\left[\begin{array}{ll}
a & c \\
0 & b
\end{array}\right] \text { or }\left[\begin{array}{ll}
a & 0 \\
c & b
\end{array}\right]} \\
& \boldsymbol{M}\left[\begin{array}{l}
x \\
y
\end{array}\right]=\left[\begin{array}{ll}
a & c \\
0 & b
\end{array}\right]\left[\begin{array}{l}
x \\
y
\end{array}\right]=\left[\begin{array}{c}
a x+c y \\
b y
\end{array}\right]
\end{aligned}
$$

- A general definition: shearing $=$ to shift the figure along a direction by an amount proportional to its signed distance from the line parallel to that direction

Shearing changes the shape (angles changes under shearing) but preserves the area


$$
a=b=1, c=1
$$

## Examples: Reflection \& Orthography

$\square$ Reflection $=$ scaling with negative factors

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



$\square$ Orthographic Projection

$$
\boldsymbol{M}=\left[\begin{array}{ll}
1 & 0 \\
0 & 0
\end{array}\right]
$$


$\square$ Does not map a basis onto another basis
$\square$ A singular transformation (can't be inverted, lost depth information along a direction)

## Example: Translation

$$
\left[\begin{array}{l}
x \\
y
\end{array}\right]+\left[\begin{array}{l}
d_{1} \\
d_{2}
\end{array}\right]=\left[\begin{array}{l}
x+d_{1} \\
y+d_{2}
\end{array}\right]
$$

Not a linear transformation (can't be represented as a matrixvector multiplication)

But if the homogeneous coordinates are used:


$$
\left[\begin{array}{lll}
1 & & d_{1} \\
& 1 & d_{2} \\
& & 1
\end{array}\right]\left[\begin{array}{l}
x \\
y \\
1
\end{array}\right]=\left[\begin{array}{c}
x+d_{1} \\
y+d_{2} \\
1
\end{array}\right]
$$

Rigid Transformation $=$ translation + rotation
$\square$ If a transformation preserves distance $\rightarrow$ called an isometry
$\square$ Rigid transformations are definitely isometries, but isometries may not be rigid
$\square$ e.g. bending a paper to a cylinder

## Example: General Projection

A general projection, or perspective transformation, or also called homography, is defined on homogeneous coordinates,

$$
\widetilde{x}^{\prime}=H \tilde{x}
$$

where $\boldsymbol{H}$ is an arbitrary $3 \times 3$ matrix, defined up to a scale.
$\square$ Converting back to inhomogeneous coordinates:

$$
x^{\prime}=\frac{h_{00} x+h_{01} y+h_{02}}{h_{20} x+h_{21} y+h_{22}} \text { and } y^{\prime}=\frac{h_{10} x+h_{11} y+h_{12}}{h_{20} x+h_{21} y+h_{22}} .
$$

$\square$ Perspective transformations preserve straight lines such that they remain straight after the transformation

## Summary of 2D Transformations*

| Transformation | Matrix | \# DoF | Preserves | Icon |
| :--- | :--- | :--- | :--- | :--- |
| translation | $[\boldsymbol{I} \mid \boldsymbol{t}]_{2 \times 3}$ | 2 | orientation |  |
| rigid (Euclidean) | $[\boldsymbol{R} \mid \boldsymbol{t}]_{2 \times 3}$ | 3 | lengths |  |
| similarity | $[s \boldsymbol{R} \mid \boldsymbol{t}]_{2 \times 3}$ | 4 | angles |  |
| affine | $[\boldsymbol{A}]_{2 \times 3}$ | 6 | parallelism |  |
| projective | $[\tilde{\boldsymbol{H}}]_{3 \times 3}$ | 8 | straight lines |  |

\#DOF : the Number of Degrees of Freedom = the number of independent variables (unknowns) that can change freely

## Summary of 3D Transformations*

| Transformation | Matrix | \# DoF | Preserves | Icon |
| :--- | :--- | :--- | :--- | :--- |
| translation | $[\boldsymbol{I} \mid \boldsymbol{t}]_{3 \times 4}$ | 3 | orientation |  |
| rigid (Euclidean) | $[\boldsymbol{R} \mid \boldsymbol{t}]_{3 \times 4}$ | 6 | lengths |  |
| similarity | $[s \boldsymbol{R} \mid \boldsymbol{t}]_{3 \times 4}$ | 7 | angles |  |
| affine | $[\boldsymbol{A}]_{3 \times 4}$ | 12 | parallelism |  |
| projective | $[\tilde{\boldsymbol{H}}]_{4 \times 4}$ | 15 | straight lines |  |

\#DOF : the Number of Degrees of Freedom $=$ the number of independent variables that can change freely

