Orthogonal Transformations

Prerequisites:

- \bullet Linear Transformations
- Dot products

A particularly important class of linear transformations on \mathbb{R}^N are the **orthogonal** transformations. Orthogonal transformations transform \mathbb{R}^N as though it was a rigid object. Thus, the lengths of lines and the angles between them are preserved. For example, rotations and reflections are orthogonal transformations.

Theorem 1: Orthogonal Transformations Let $f: \mathbb{R}^N \longrightarrow \mathbb{R}^N$ be a linear transformation, equivalent to multiplication by the matrix $\boxed{\mathsf{F}}$. The following are equivalent:

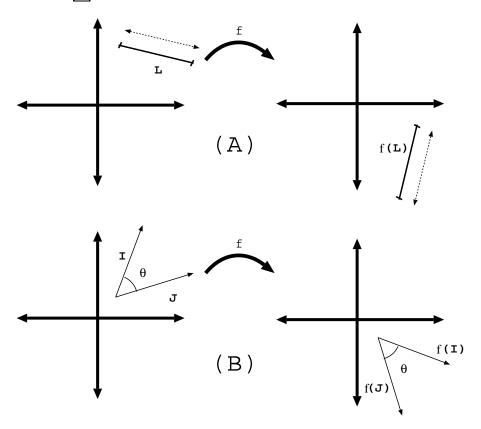


Figure 1: Orthogonal transformations preserves lengths and angles

1. f preserves lengths and angles. In other words, if $\mathbb L$ is a line-segment in $\mathbb R^N$, then $\ell_{\it mgth} \, [f(\mathbb{L})] \, = \ell_{\it mgth} \, [\mathbb{L}]$ (see ${f Part} \, \, ({f A})$ of Figure 1). If \mathbb{I} and \mathbb{J} are two line-segments which intersect with an angle of θ between them, then the line segments $f(\mathbb{I})$ and $f(\mathbb{J})$ also intersect with an angle of θ (see **Part** (**B**) of Figure 1 on the page before).

2. f preserves the dot products of vectors. In other words, for any $\mathbf{v},\mathbf{w}\in\mathbb{R}^N$,

$$(f(\mathbf{v})) \bullet (f(\mathbf{w})) = \mathbf{v} \bullet \mathbf{w}$$

- 3. If $\mathcal{B} = \{\mathbf{b}_1, \dots, \mathbf{b}_N\}$ is any **orthonormal basis** for \mathbb{R}^N , then $\{f(\mathbf{b}_1), \dots, f(\mathbf{b}_N)\}$ is *also* an orthonormal basis for \mathbb{R}^N .
- 4. If $\boxed{\mathsf{F}} = \begin{bmatrix} \uparrow & \uparrow & \dots & \uparrow \\ \mathbf{c}_1 & \mathbf{c}_2 & \dots & \mathbf{c}_N \\ \downarrow & \downarrow & \dots & \downarrow \end{bmatrix}$, then the column vectors $\{\mathbf{c}_1,\dots,\mathbf{c}_N\}$ form an orthonormal basis for \mathbb{R}^N .
- 5. $\left[\mathsf{F}\right]^{-1} = \left[\mathsf{F}\right]^{t}$
- 6. If $\boxed{\mathsf{F}} = \begin{bmatrix} \leftarrow & \mathbf{r}_1 & \longrightarrow \\ \leftarrow & \mathbf{r}_2 & \longrightarrow \\ \vdots & \vdots & \vdots \\ \leftarrow & \mathbf{r}_N & \longrightarrow \end{bmatrix}$, then the row vectors $\{\mathbf{r}_1, \dots, \mathbf{r}_N\}$ form an orthonormal basis for \mathbb{R}^N

Proof:

Proof of "(1) \iff (2)": Recall that the *length* of a vector \mathbf{v} is given by: $\|\mathbf{v}\| = \sqrt{\mathbf{v} \cdot \mathbf{v}}$, and that the *angle* between two vectors is given:

$$angle(\mathbf{v}, \mathbf{w}) = \arccos\left(\frac{\mathbf{v} \bullet \mathbf{w}}{\|\mathbf{v}\| \cdot \|\mathbf{w}\|}\right)$$

Thus, a linear transformation preserves all angles and all lengths if and only if it preserves all dot products.

Proof of "(2) \Longrightarrow (3)": If $\{\mathbf{b}_1, \ldots, \mathbf{b}_N\}$ is an orthonormal set, and f preserves all inner products, then $\{f(\mathbf{b}_1), \ldots, f(\mathbf{b}_N)\}$ must also be an orthonormal set, because for any i, j,

$$f(\mathbf{b}_i) \bullet f(\mathbf{b}_i) = \mathbf{i} \bullet \mathbf{j}$$

Proof of "(3) \Longrightarrow (4)": Let $\mathcal{E} = \{\mathbf{e}_1, \dots, \mathbf{e}_N\}$ be the standard basis. Then \mathcal{E} is an orthonormal basis; thus $\{f(\mathbf{e}_1), \dots, f(\mathbf{e}_N)\}$ must also be an orthonormal basis. But $f(\mathbf{e}_1) = \mathbf{c}_1, \dots, f(\mathbf{e}_N) = \mathbf{c}_N$.

Proof of "(4) \Longrightarrow (2)": Let $\mathbf{v}=(v_1,\ldots,v_N)$ and $\mathbf{w}=(w_1,\ldots,w_N)$ be vectors in \mathbb{R}^N . Then

$$(f(\mathbf{v})) \bullet (f(\mathbf{w})) = \left(f\left(\sum_{n=1}^{N} v_n \mathbf{e}_n\right) \right) \bullet \left(f\left(\sum_{m=1}^{N} w_m \mathbf{e}_m\right) \right)$$

$$=_{(1)} \left(\sum_{n=1}^{N} v_n f(\mathbf{e}_n) \right) \bullet \left(\sum_{m=1}^{N} w_m f(\mathbf{e}_m) \right)$$

$$=_{(2)} \left(\sum_{n=1}^{N} v_n \mathbf{c}_n \right) \bullet \left(\sum_{m=1}^{N} w_m \mathbf{c}_m \right)$$

$$=_{(3)} \sum_{n=1}^{N} \sum_{m=1}^{N} v_n w_m \left(\mathbf{c}_n \bullet \mathbf{c}_m \right)$$

$$=_{(4)} \sum_{n=1}^{N} v_n w_n$$

$$= \mathbf{v} \bullet \mathbf{w}$$

- (1) Because f is linear.
- (2) Because $f(\mathbf{e}_n) = \mathbf{c}_n$.
- (3) Because distributes through addition.
- (4) Because $\{\mathbf{c}_1, \dots, \mathbf{c}_N\}$ is an orthonormal set.

Proof of "(4) \iff (5)": Consider the matrix $\boxed{\mathbf{A}} = \boxed{\mathbf{F}}^t \cdot \boxed{\mathbf{F}}$. Now,

$$\begin{bmatrix}
\mathbf{F} \\
 \end{bmatrix} = \begin{bmatrix}
\uparrow & \uparrow & \dots & \uparrow \\
\mathbf{c}_1 & \mathbf{c}_2 & \dots & \mathbf{c}_N \\
\downarrow & \downarrow & \dots & \downarrow
\end{bmatrix}, \quad \text{while } \begin{bmatrix}
\mathbf{F}
\end{bmatrix}^t = \begin{bmatrix}
\leftarrow & \mathbf{c}_1 & \longrightarrow \\
\leftarrow & \mathbf{c}_2 & \longrightarrow \\
\vdots & \vdots & \vdots \\
\leftarrow & \mathbf{c}_N & \longrightarrow
\end{bmatrix}$$

Thus, if a_{ij} is the (i,j)th entry of A, then

$$a_{ij} = \mathbf{c}_i \bullet \mathbf{c}_j.$$

Hence,

$$\left(\begin{bmatrix} \mathbf{F} \end{bmatrix}^{-1} = \begin{bmatrix} \mathbf{F} \end{bmatrix}^{t} \right) \iff \left(\begin{bmatrix} \mathbf{A} \end{bmatrix} = \begin{bmatrix} \mathbf{F} \end{bmatrix}^{t} \cdot \begin{bmatrix} \mathbf{F} \end{bmatrix} = \begin{bmatrix} \mathbf{Id} \end{bmatrix} \right)$$

$$\iff \left(\begin{bmatrix} a_{ij} \end{bmatrix} = \begin{bmatrix} 1 & if & i = j \\ 0 & if & i \neq j \end{bmatrix} \right)$$

$$\iff \left(\mathbf{c}_i \bullet \mathbf{c}_j = \left\{ \begin{array}{l} 1 & if \quad i = j \\ 0 & if \quad i \neq j \end{array} \right)$$

$$\iff \left(\left\{ \mathbf{c}_1, \dots, \mathbf{c}_N \right\} \text{ are an orthonormal basis } \right).$$

Proof of "(5) \iff (6)": The proof is identical to "(4) \iff (5)"; now consider the matrix $\boxed{\mathbf{A}} = \boxed{\mathbf{F}} \cdot \boxed{\mathbf{F}}^t$, and show that this matrix is the identity if and only if the *row vectors* of $\boxed{\mathbf{F}}$ are orthonormal.

 $_{\square}$ [Theorem 1]

Definition 2: Orthogonal Transformation

Let $f: \mathbb{R}^N \longrightarrow \mathbb{R}^N$ be a linear transformation. f is called an **orthogonal transformation** if it satisfies any (and thus, *all*) of the conditions of the previous theorem.

If F is the matrix of an orthogonal transformation, then we say F is an orthogonal matrix.

Examples 3:

- 1. The **identity map** is an orthogonal transformation.
- 2. If $\theta \in [0, 2\pi]$, and $f : \mathbb{R}^2 \longrightarrow \mathbb{R}^2$ is **rotation by** θ about the origin, then f is an orthogonal transformation. The matrix of f is

$$\begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix}$$

Thus, the vectors $[\cos(\theta), \sin(\theta)]$ and $[-\sin(\theta), \cos(\theta)]$ form an orthonormal basis for \mathbb{R}^2 .

3. If $\theta \in [0, 2\pi]$, and $f : \mathbb{R}^3 \longrightarrow \mathbb{R}^3$ is **rotation by** θ about the second ("y") axis, then f is an orthogonal transformation. The matrix of f is

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

Thus, the vectors $[\cos(\theta), 0, \sin(\theta)], [0, 1, 0], \text{ and } [-\sin(\theta), 0, \cos(\theta)]$ form an orthonormal basis for \mathbb{R}^3 .

4. If $\mathbb{V} \subset \mathbb{R}^N$ is a linear subspace, and $f: \mathbb{R}^N \longrightarrow \mathbb{R}^N$ is the **reflection** across \mathbb{V} :

$$f(\mathbf{v}) = 2\mathbf{pr}_{\mathbb{V}}(\mathbf{v}) - \mathbf{v},$$

then f is an orthogonal transformation.

Remark 4:

- 1. If $f,g:\mathbb{R}^N\longrightarrow\mathbb{R}^N$ are orthogonal transformations, then so are f^{-1} and $f\circ g.$
- 2. If A, B are orthogonal $N \times N$ matrices then so are A and $A \cdot B$.
- 3. If A is the matrix of an orthogonal transformation f, then A is also the matrix of an orthogonal transformation: f^{-1} .
- 4. Suppose $g: \mathbb{R}^N \longrightarrow \mathbb{R}^N$ is some linear transformation, whose matrix representation (relative to the standard basis) is $\boxed{\mathbf{G}}$. Suppose \mathcal{B} is an orthonormal basis for \mathbb{R}^N , and we want to compute the matrix representation of g with respect to \mathcal{B} . Let $\boxed{\mathbf{B}}$ be the matrix whose **column vectors** are the elements of \mathcal{B} . Then we know that

$$\widetilde{\mathbb{G}} = \mathbb{B}^{-1} \cdot \mathbb{G} \cdot \mathbb{B}$$

is the matrix representation of g with respect to \mathcal{B} . But $\boxed{\mathbf{B}}$ is an orthogonal matrix, hence $\boxed{\mathbf{B}}^{-1} = \boxed{\mathbf{B}}^t$. Hence, the matrix representation of g relative to \mathcal{B} can also be written:

$$\widetilde{\mathbf{G}} = \mathbf{B}^t \cdot \mathbf{G} \cdot \mathbf{B}$$