

Linear Algebra 2

Lecture #18

Permutation matrices. Orthogonal matrices

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- This lecture has three parts:

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 - ① Permutation matrices

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 - ① Permutation matrices
 - ② Orthogonal matrices
 - ③ Scalar product, coordinate vectors, and matrices of linear functions

1 Permutation matrices

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Definition

A *permutation matrix* is a square matrix that has exactly one 1 in each row and each column, and has 0's everywhere else.

- Examples:

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix} \quad \begin{bmatrix} 0 & 0 & 1 \\ 0 & 1 & 0 \\ 1 & 0 & 0 \end{bmatrix}$$

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- The 0's and 1's in permutation matrices may belong to any field \mathbb{F} of our choice.
 - In our study of permutation matrices, we will never need to add two non-zero numbers, and whenever we multiply two numbers, at least one of the two numbers will be 0 or 1.
 - So, it does not matter which particular field we are working in, and therefore, we will not emphasize this.

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- Moreover, $n \times n$ permutation matrices are precisely the matrices that can be obtained from the identity matrix I_n by reordering (i.e. permuting) rows, or alternatively, by reordering (i.e. permuting) columns.
- So, the columns of an $n \times n$ permutation matrix are the standard basis vectors $\mathbf{e}_1, \dots, \mathbf{e}_n$ (appearing in some order in that matrix), whereas the rows are $\mathbf{e}_1^T, \dots, \mathbf{e}_n^T$ (again, appearing in some order in that matrix).

Definition

For a positive integer n and a permutation $\pi \in S_n$, we define the *matrix of the permutation* π , denoted by P_π , to be the $n \times n$ matrix that has 1 in the $(i, \pi(i))$ -th entry for each each index $i \in \{1, \dots, n\}$, and has 0 in all other entries. In other words, for each index $i \in \{1, \dots, n\}$, the i -th row of the matrix P_π is $\mathbf{e}_{\pi(i)}^T$.

- For example, for the permutation

$$\pi = \begin{pmatrix} 1 & 2 & 3 & 4 & 5 & 6 \\ 2 & 4 & 1 & 6 & 5 & 3 \end{pmatrix},$$

in S_6 , we obtain the 6×6 permutation matrix

$$P_\pi = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix}.$$

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- Obviously, for a positive integer n , the matrix of the identity permutation 1_n in S_n is precisely the identity matrix I_n , i.e. $P_{1_n} = I_n$.

Proposition 2.3.10

Let n be a positive integer, and let $\pi \in S_n$. Then P_π is a permutation matrix.

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 - The answer to this question is “yes,” and it follows from a simple counting argument, as follows.
 - Let n be a positive integer.
 - The $n \times n$ permutation matrices are precisely those $n \times n$ matrices whose columns are the standard basis vectors $\mathbf{e}_1, \dots, \mathbf{e}_n$, appearing in some order. There are $n!$ many ways to order the vectors $\mathbf{e}_1, \dots, \mathbf{e}_n$, and consequently, there are $n!$ many $n \times n$ permutation matrices.

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 - So, the number of $n \times n$ permutation matrices is the same as the number of matrices of permutations in S_n .

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 - On the other hand, $|S_n| = n!$, and consequently, there are $n!$ many matrices of permutations in S_n .
 - We are using the fact that different permutations have different matrices.
 - So, the number of $n \times n$ permutation matrices is the same as the number of matrices of permutations in S_n .
 - It now follows from Proposition 2.3.10 that $n \times n$ permutation matrices are precisely the matrices of permutations in S_n .

- Reminder:

Proposition 1.4.5

Let \mathbb{F} be a field, and let $A = \begin{bmatrix} \mathbf{a}_1 & \dots & \mathbf{a}_m \end{bmatrix}$ be a matrix in $\mathbb{F}^{n \times m}$. Then for all indices $i \in \{1, \dots, m\}$, we have that $A\mathbf{e}_i^m = \mathbf{a}_i$.

Proposition 1.8.2

Let \mathbb{F} be a field, and let

$$A = \begin{bmatrix} \mathbf{r}_1 \\ \vdots \\ \mathbf{r}_n \end{bmatrix}$$

be a matrix in $\mathbb{F}^{n \times m}$. Then for all $i \in \{1, \dots, n\}$, we have that

$$\mathbf{e}_i^T A = \mathbf{r}_i,$$

where \mathbf{e}_i is the i -th standard basis vector of \mathbb{F}^n .

Proposition 2.3.11

Let n be a positive integer, and let $\pi \in S_n$ be a permutation. Then both the following hold:

- Ⓐ $\forall i \in \{1, \dots, n\}$: $\mathbf{e}_i^T P_\pi = \mathbf{e}_{\pi(i)}$, i.e. the i -th row of P_π is $\mathbf{e}_{\pi(i)}^T$;
- Ⓑ $\forall j \in \{1, \dots, n\}$: $P_\pi \mathbf{e}_j = \mathbf{e}_{\pi^{-1}(j)}$, i.e. the j -th column of P_π is $\mathbf{e}_{\pi^{-1}(j)}$.

Consequently, in terms of its rows and columns, P_π can be written as follows:

$$P_\pi = \begin{bmatrix} \mathbf{e}_{\pi(1)}^T \\ \vdots \\ \mathbf{e}_{\pi(n)}^T \end{bmatrix} = \begin{bmatrix} \mathbf{e}_{\pi^{-1}(1)} & \dots & \mathbf{e}_{\pi^{-1}(n)} \end{bmatrix}.$$

Proof. The last statement of the proposition follows immediately from (a) and (b). So, it is enough to prove (a) and (b).

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- Ⓐ $\forall i \in \{1, \dots, n\}: \mathbf{e}_i^T P_\pi = \mathbf{e}_{\pi(i)}$, i.e. the i -th row of P_π is $\mathbf{e}_{\pi(i)}$;
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Proof (continued). (a) Fix an index $i \in \{1, \dots, n\}$. By Proposition 1.8.2, $\mathbf{e}_i^T P_\pi$ is precisely the i -th row of the matrix P_π , and by the definition of the matrix P_π , its i -th row is precisely $\mathbf{e}_{\pi(i)}$.

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(b) Fix an index $j \in \{1, \dots, n\}$.

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(b) Fix an index $j \in \{1, \dots, n\}$. By Proposition 1.4.5, $P_\pi \mathbf{e}_j$ is precisely the j -th column of the matrix P_π . Set $i := \pi^{-1}(j)$, so that $j = \pi(i)$.

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- (a) $\forall i \in \{1, \dots, n\}$: $\mathbf{e}_i^T P_\pi = \mathbf{e}_{\pi(i)}$, i.e. the i -th row of P_π is $\mathbf{e}_{\pi(i)}^T$;
- (b) $\forall j \in \{1, \dots, n\}$: $P_\pi \mathbf{e}_j = \mathbf{e}_{\pi^{-1}(j)}$, i.e. the j -th column of P_π is $\mathbf{e}_{\pi^{-1}(j)}$.

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(b) Fix an index $j \in \{1, \dots, n\}$. By Proposition 1.4.5, $P_\pi \mathbf{e}_j$ is precisely the j -th column of the matrix P_π . Set $i := \pi^{-1}(j)$, so that $j = \pi(i)$. By (a), the i -th row of P_π is the row vector $\mathbf{e}_{\pi(i)}^T = \mathbf{e}_j^T$. So, P_π has 1 in its (i, j) -th entry. Since P_π is a permutation matrix (by Proposition 2.3.10), and therefore has exactly one 1 in each column, it follows that the j -th column of P_π is $\mathbf{e}_i = \mathbf{e}_{\pi^{-1}(j)}$. \square

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Let n be a positive integer, and let $\pi \in S_n$ be a permutation. Then both the following hold:

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Consequently, in terms of its rows and columns, P_π can be written as follows:

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Proof. We have that

$$P_{\pi}^T \stackrel{(*)}{=} \left(\left[\mathbf{e}_{\pi^{-1}(1)} \quad \dots \quad \mathbf{e}_{\pi^{-1}(n)} \right] \right)^T = \begin{bmatrix} \mathbf{e}_{\pi^{-1}(1)}^T \\ \vdots \\ \mathbf{e}_{\pi^{-1}(n)}^T \end{bmatrix} \stackrel{(*)}{=} P_{\pi^{-1}},$$

where both instances of $(*)$ follow from Proposition 2.3.11. \square

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Let n be a positive integer, and let σ and π be permutations in S_n .
Then $P_{\sigma \circ \pi} = P_\pi P_\sigma$.

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Proof. It suffices to show that matrices $P_{\sigma \circ \pi}$ and $P_\pi P_\sigma$ have the same corresponding rows. Fix an index $i \in \{1, \dots, n\}$. By Proposition 1.8.2, the i -th row of the matrix $P_{\sigma \circ \pi}$ is $\mathbf{e}_i^T P_{\sigma \circ \pi}$, and the i -th row of the matrix $P_\pi P_\sigma$ is $\mathbf{e}_i^T (P_\pi P_\sigma)$.

Proposition 2.3.11

(a) $\forall i \in \{1, \dots, n\}$: $\mathbf{e}_i^T P_\pi = \mathbf{e}_{\pi(i)}$, i.e. the i -th row of P_π is $\mathbf{e}_{\pi(i)}^T$;

Proposition 2.3.13

Let n be a positive integer, and let σ and π be permutations in S_n . Then $P_{\sigma \circ \pi} = P_\pi P_\sigma$.

Proof. It suffices to show that matrices $P_{\sigma \circ \pi}$ and $P_\pi P_\sigma$ have the same corresponding rows. Fix an index $i \in \{1, \dots, n\}$. By Proposition 1.8.2, the i -th row of the matrix $P_{\sigma \circ \pi}$ is $\mathbf{e}_i^T P_{\sigma \circ \pi}$, and the i -th row of the matrix $P_\pi P_\sigma$ is $\mathbf{e}_i^T (P_\pi P_\sigma)$. So, we just need to show that $\mathbf{e}_i^T P_{\sigma \circ \pi} = \mathbf{e}_i^T (P_\pi P_\sigma)$.

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$$\begin{aligned} \mathbf{e}_i^T (P_\pi P_\sigma) &= (\mathbf{e}_i^T P_\pi) P_\sigma \stackrel{(*)}{=} \mathbf{e}_{\pi(i)}^T P_\sigma \stackrel{(*)}{=} \mathbf{e}_{\sigma(\pi(i))} \\ &= \mathbf{e}_{(\sigma \circ \pi)(i)}^T \stackrel{(*)}{=} \mathbf{e}_i^T P_{\sigma \circ \pi}, \end{aligned}$$

where all three instances of (*) follow from Prop. 2.3.11(a). \square

Theorem 2.3.14

Let n be a positive integer, and let $\pi \in S_n$. Then P_π is invertible, and moreover,

$$P_\pi^{-1} = P_{\pi^{-1}} = P_\pi^T.$$

Proof.

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We now compute:

$$P_\pi P_{\pi^{-1}} \stackrel{(*)}{=} P_{\pi^{-1} \circ \pi} = P_{1_n} = I_n,$$

where (*) follows immediately from Proposition 2.3.13.

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Let n be a positive integer, and let $\pi \in S_n$. Then P_π is invertible, and moreover,

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where (*) follows immediately from Proposition 2.3.13.

Analogously, $P_{\pi^{-1}} P_\pi = I_n$. So, P_π and $P_{\pi^{-1}}$ are invertible and are each other's inverses. This completes the argument. \square

Theorem 2.3.14

Let n be a positive integer, and let $\pi \in S_n$. Then P_π is invertible, and moreover,

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- **Remark:** A matrix $Q \in \mathbb{R}^{n \times n}$ is *orthogonal* if it satisfies $Q^T Q = I_n$.
 - Theorem 2.3.14 guarantees that permutation matrices are orthogonal (as long as we consider the 0's and 1's in those matrices as belonging to \mathbb{R} , rather than to some other field).

- As our next theorem (Theorem 2.3.15, next slide) shows, multiplying a matrix by a permutation matrix on the left permutes the rows of the original matrix.

- As our next theorem (Theorem 2.3.15, next slide) shows, multiplying a matrix by a permutation matrix on the left permutes the rows of the original matrix.
- On the other hand, multiplying a matrix by a permutation matrix on the right permutes the columns of the original matrix.

Theorem 2.3.15

Let $A = \begin{bmatrix} \mathbf{r}_1 \\ \vdots \\ \mathbf{r}_n \end{bmatrix} = [\mathbf{a}_1 \ \dots \ \mathbf{a}_m]$ be an $n \times m$ matrix with entries in some field \mathbb{F} . Then all the following hold:

(a) for all $\pi \in S_n$, we have that

$$P_\pi A = \begin{bmatrix} \mathbf{r}_{\pi(1)} \\ \vdots \\ \mathbf{r}_{\pi(n)} \end{bmatrix};$$

(b) for all $\pi \in S_m$, we have that

$$AP_\pi = [\mathbf{a}_{\pi^{-1}(1)} \ \dots \ \mathbf{a}_{\pi^{-1}(m)}];$$

(c) for all $\pi \in S_m$, we have that

$$AP_\pi^T = [\mathbf{a}_{\pi(1)} \ \dots \ \mathbf{a}_{\pi(m)}].$$

Proof.

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$$AP_\pi = [\mathbf{a}_{\pi^{-1}(1)} \quad \dots \quad \mathbf{a}_{\pi^{-1}(m)}];$$

(c) for all $\pi \in S_m$, we have that

$$AP_\pi^T = [\mathbf{a}_{\pi(1)} \quad \dots \quad \mathbf{a}_{\pi(m)}].$$

Proof. We prove (b). Parts (a) and (c) are in the Lecture Notes.

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Proof of (b).

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(b) for all $\pi \in S_m$, we have that

$$AP_\pi = [\mathbf{a}_{\pi^{-1}(1)} \quad \dots \quad \mathbf{a}_{\pi^{-1}(m)}];$$

Proof of (b). Fix any permutation $\pi \in S_m$. In what follows, $\mathbf{e}_1, \dots, \mathbf{e}_m$ are the standard basis vectors of \mathbb{F}^m . We compute:

$$AP_\pi = A [\mathbf{e}_{\pi^{-1}(1)} \quad \dots \quad \mathbf{e}_{\pi^{-1}(m)}] \quad \text{by Proposition 2.3.11}$$

$$= [A\mathbf{e}_{\pi^{-1}(1)} \quad \dots \quad A\mathbf{e}_{\pi^{-1}(m)}] \quad \text{by the definition of matrix multiplication}$$

$$= [\mathbf{a}_{\pi^{-1}(1)} \quad \dots \quad \mathbf{a}_{\pi^{-1}(m)}] \quad \text{by Proposition 1.4.5.}$$

This proves (b). \square

Theorem 2.3.15

Let $A = \begin{bmatrix} \mathbf{r}_1 \\ \vdots \\ \mathbf{r}_n \end{bmatrix} = [\mathbf{a}_1 \ \dots \ \mathbf{a}_m]$ be an $n \times m$ matrix with entries in some field \mathbb{F} . Then all the following hold:

(a) for all $\pi \in S_n$, we have that

$$P_\pi A = \begin{bmatrix} \mathbf{r}_{\pi(1)} \\ \vdots \\ \mathbf{r}_{\pi(n)} \end{bmatrix};$$

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(c) for all $\pi \in S_m$, we have that

$$AP_\pi^T = [\mathbf{a}_{\pi(1)} \ \dots \ \mathbf{a}_{\pi(m)}].$$

② Orthogonal matrices

2 Orthogonal matrices

- In our study of orthogonal matrices, we assume that \mathbb{R}^n is equipped with the standard scalar product \cdot and the induced norm $\|\cdot\|$.

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Definition

A matrix $Q \in \mathbb{R}^{n \times n}$ is *orthogonal* if it satisfies $Q^T Q = I_n$.

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Let n be a positive integer, and let $\pi \in S_n$. Then P_π is invertible, and moreover,

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Let n be a positive integer, and let $\pi \in S_n$. Then P_π is invertible, and moreover,

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- The matrices mentioned so far all have entries only $-1, 0, 1$. However, there are many other orthogonal matrices, and we will see a couple of examples later.

- Reminder:

Corollary 3.3.18

Let \mathbb{F} be field, and let $A, B \in \mathbb{F}^{n \times n}$ be such that $AB = I_n$ or $BA = I_n$. Then $AB = BA = I_n$, i.e. A and B are both invertible and are each other's inverses.

Theorem 6.8.1

Let $Q \in \mathbb{R}^{n \times n}$. Then the following are equivalent:

- (a) Q is orthogonal (i.e. satisfies $Q^T Q = I_n$);
- (b) Q is invertible and satisfies $Q^{-1} = Q^T$;
- (c) $Q Q^T = I_n$;
- (d) Q^T is orthogonal;
- (e) Q is invertible and Q^{-1} is orthogonal;
- (f) the columns of Q form an orthonormal basis of \mathbb{R}^n ;
- (g) the columns of Q^T form an orthonormal basis of \mathbb{R}^n .

Proof.

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Proof. By Corollary 3.3.18, we have that (a), (b), and (c) are equivalent.

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Proof. By Corollary 3.3.18, we have that (a), (b), and (c) are equivalent. Moreover, since $(Q^T)^T = Q$, we have that (c) and (d) are equivalent. This proves that (a), (b), (c), and (d) are equivalent.

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Proof (continued). Next, (b) and (d) together imply (e).

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Proof (continued). Next, (b) and (d) together imply (e).

Suppose now that (e) holds. Then by applying “(a) \implies (b)” to the matrix Q^{-1} , we see that Q^{-1} is invertible and satisfies $(Q^{-1})^{-1} = (Q^{-1})^T$. Consequently, $Q^{-1} = Q^T$, and it follows that (b) holds.

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Proof (continued). So far, we have established that (a), (b), (c), (d), and (e) are equivalent.

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Proof (continued). So far, we have established that (a), (b), (c), (d), and (e) are equivalent.

Let us now show that (a) and (f) are equivalent.

Theorem 6.8.1

- Ⓐ Q is orthogonal (i.e. satisfies $Q^T Q = I_n$);
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Proof (continued).

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Proof (continued). Set $Q = \begin{bmatrix} \mathbf{q}_1 & \dots & \mathbf{q}_n \end{bmatrix}$. Then

$$\begin{aligned} Q^T Q &= \begin{bmatrix} \mathbf{q}_1^T \\ \mathbf{q}_2^T \\ \vdots \\ \mathbf{q}_n^T \end{bmatrix} \begin{bmatrix} \mathbf{q}_1 & \mathbf{q}_2 & \dots & \mathbf{q}_n \end{bmatrix} \\ &= \begin{bmatrix} \mathbf{q}_1 \cdot \mathbf{q}_1 & \mathbf{q}_1 \cdot \mathbf{q}_2 & \dots & \mathbf{q}_1 \cdot \mathbf{q}_n \\ \mathbf{q}_2 \cdot \mathbf{q}_1 & \mathbf{q}_2 \cdot \mathbf{q}_2 & \dots & \mathbf{q}_2 \cdot \mathbf{q}_n \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{q}_n \cdot \mathbf{q}_1 & \mathbf{q}_n \cdot \mathbf{q}_2 & \dots & \mathbf{q}_n \cdot \mathbf{q}_n \end{bmatrix}. \end{aligned}$$

Theorem 6.8.1

- Ⓐ Q is orthogonal (i.e. satisfies $Q^T Q = I_n$);
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Proof (continued). Set $Q = \begin{bmatrix} \mathbf{q}_1 & \dots & \mathbf{q}_n \end{bmatrix}$. Then

$$\begin{aligned} Q^T Q &= \begin{bmatrix} \mathbf{q}_1^T \\ \mathbf{q}_2^T \\ \vdots \\ \mathbf{q}_n^T \end{bmatrix} \begin{bmatrix} \mathbf{q}_1 & \mathbf{q}_2 & \dots & \mathbf{q}_n \end{bmatrix} \\ &= \begin{bmatrix} \mathbf{q}_1 \cdot \mathbf{q}_1 & \mathbf{q}_1 \cdot \mathbf{q}_2 & \dots & \mathbf{q}_1 \cdot \mathbf{q}_n \\ \mathbf{q}_2 \cdot \mathbf{q}_1 & \mathbf{q}_2 \cdot \mathbf{q}_2 & \dots & \mathbf{q}_2 \cdot \mathbf{q}_n \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{q}_n \cdot \mathbf{q}_1 & \mathbf{q}_n \cdot \mathbf{q}_2 & \dots & \mathbf{q}_n \cdot \mathbf{q}_n \end{bmatrix}. \end{aligned}$$

So, $Q^T Q = I_n$ iff $\{\mathbf{q}_1, \dots, \mathbf{q}_n\}$ is an orthonormal set.

Theorem 6.8.1

- Ⓐ Q is orthogonal (i.e. satisfies $Q^T Q = I_n$);
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Proof (continued). Set $Q = \begin{bmatrix} \mathbf{q}_1 & \dots & \mathbf{q}_n \end{bmatrix}$. Then

$$\begin{aligned} Q^T Q &= \begin{bmatrix} \mathbf{q}_1^T \\ \mathbf{q}_2^T \\ \vdots \\ \mathbf{q}_n^T \end{bmatrix} \begin{bmatrix} \mathbf{q}_1 & \mathbf{q}_2 & \dots & \mathbf{q}_n \end{bmatrix} \\ &= \begin{bmatrix} \mathbf{q}_1 \cdot \mathbf{q}_1 & \mathbf{q}_1 \cdot \mathbf{q}_2 & \dots & \mathbf{q}_1 \cdot \mathbf{q}_n \\ \mathbf{q}_2 \cdot \mathbf{q}_1 & \mathbf{q}_2 \cdot \mathbf{q}_2 & \dots & \mathbf{q}_2 \cdot \mathbf{q}_n \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{q}_n \cdot \mathbf{q}_1 & \mathbf{q}_n \cdot \mathbf{q}_2 & \dots & \mathbf{q}_n \cdot \mathbf{q}_n \end{bmatrix}. \end{aligned}$$

So, $Q^T Q = I_n$ iff $\{\mathbf{q}_1, \dots, \mathbf{q}_n\}$ is an orthonormal set. But by Proposition 6.3.4(b), any orthonormal set of n vectors in \mathbb{R}^n is in fact an orthonormal basis of \mathbb{R}^n . So, (a) and (f) are equivalent.

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Let $Q \in \mathbb{R}^{n \times n}$. Then the following are equivalent:

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- (c) $Q Q^T = I_n$;
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- (e) Q is invertible and Q^{-1} is orthogonal;
- (f) the columns of Q form an orthonormal basis of \mathbb{R}^n ;
- (g) the columns of Q^T form an orthonormal basis of \mathbb{R}^n .

Proof (continued). Analogously to “(a) \iff (f),” we have that (d) and (g) are equivalent. \square

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Let $Q \in \mathbb{R}^{n \times n}$. Then the following are equivalent:

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- (e) Q is invertible and Q^{-1} is orthogonal;
- (f) the columns of Q form an orthonormal basis of \mathbb{R}^n ;
- (g) the columns of Q^T form an orthonormal basis of \mathbb{R}^n .

- We can make new orthogonal matrices out of old ones, as Propositions 6.8.2, 6.8.3, and 6.8.4 (below and next slide) show.
- The proofs of these propositions are easy and are in the Lecture Notes (we omit them here).

Proposition 6.8.2

Let

$$Q = [\mathbf{q}_1 \quad \dots \quad \mathbf{q}_n] = \begin{bmatrix} \mathbf{r}_1^T \\ \vdots \\ \mathbf{r}_n^T \end{bmatrix}$$

be an orthogonal matrix in \mathbb{R}^n . Then all the following hold:

- Ⓐ $\forall \alpha_1, \dots, \alpha_n \in \{-1, 1\}$: $[\alpha_1 \mathbf{q}_1 \quad \dots \quad \alpha_n \mathbf{q}_n]$ is orthogonal;
- Ⓑ $\forall \alpha_1, \dots, \alpha_n \in \{-1, 1\}$: $\begin{bmatrix} \alpha_1 \mathbf{r}_1^T \\ \vdots \\ \alpha_n \mathbf{r}_n^T \end{bmatrix}$ is orthogonal;
- Ⓒ the matrix $-Q$ is orthogonal.

Proposition 6.8.3

If $Q_1, Q_2 \in \mathbb{R}^{n \times n}$ are orthogonal, then so is their product $Q_1 Q_2$.

Proposition 6.8.4

Let $Q_1 \in \mathbb{R}^{m \times m}$ and $Q_2 \in \mathbb{R}^{n \times n}$ be orthogonal matrices. Then the $(m+n) \times (m+n)$ matrix

$$Q = \begin{bmatrix} Q_1 & O_{m \times n} \\ O_{n \times m} & Q_2 \end{bmatrix}$$

is an orthogonal matrix in $\mathbb{R}^{(m+n) \times (m+n)}$.

- Next, we discuss two particularly significant orthogonal matrices: the Householder matrix and the Givens matrix.

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- Reminder:

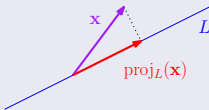
Corollary 6.6.4

Let \mathbf{a} be a non-zero vector in \mathbb{R}^n . Then the standard matrix of orthogonal projection onto the line $L := \text{Span}(\mathbf{a})$ is the matrix

$$\mathbf{a}(\mathbf{a}^T \mathbf{a})^{-1} \mathbf{a}^T = \mathbf{a}(\mathbf{a} \cdot \mathbf{a})^{-1} \mathbf{a}^T = \frac{1}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T.$$

Consequently, for every vector $\mathbf{x} \in \mathbb{R}^n$, we have that

$$\mathbf{x}_L = \text{proj}_L(\mathbf{x}) = \frac{1}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T \mathbf{x}.$$



Definition

For a non-zero vector \mathbf{a} in \mathbb{R}^n , the *Householder matrix* is the $n \times n$ matrix

$$H(\mathbf{a}) := I_n - \frac{2}{\mathbf{a}^T \mathbf{a}} \mathbf{a} \mathbf{a}^T = I_n - \frac{2}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T.$$

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- To see that $H(\mathbf{a})$ is an orthogonal matrix, we compute:

$$\begin{aligned} H(\mathbf{a})^T H(\mathbf{a}) &= (I_n - \frac{2}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T)^T (I_n - \frac{2}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T) \\ &= (I_n^T - \frac{2}{\mathbf{a} \cdot \mathbf{a}} (\mathbf{a} \mathbf{a}^T)^T) (I_n - \frac{2}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T) \\ &= (I_n - \frac{2}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T) (I_n - \frac{2}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T) \\ &= I_n - \frac{4}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T + \frac{4}{(\mathbf{a} \cdot \mathbf{a})^2} \underbrace{\mathbf{a} \mathbf{a}^T \mathbf{a} \mathbf{a}^T}_{=\mathbf{a} \cdot \mathbf{a}} \\ &= I_n - \frac{4}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T + \frac{4}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T \\ &= I_n. \end{aligned}$$

- Let us now discuss the geometric meaning of this matrix.

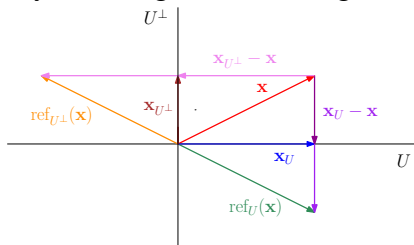
- Let us now discuss the geometric meaning of this matrix.
- First of all, we observe that if U is a subspace of \mathbb{R}^n , then for any vector $\mathbf{x} \in \mathbb{R}^n$, the reflection of \mathbf{x} about U is given by

$$\text{ref}_U(\mathbf{x}) := \mathbf{x} + 2(\mathbf{x}_U - \mathbf{x}) = 2\mathbf{x}_U - \mathbf{x},$$

and the reflection of \mathbf{x} about U^\perp is given by

$$\text{ref}_{U^\perp}(\mathbf{x}) := \mathbf{x} + 2(\mathbf{x}_{U^\perp} - \mathbf{x}) \stackrel{(*)}{=} \mathbf{x} - 2\mathbf{x}_U = -\text{ref}_U(\mathbf{x}),$$

where (*) follows from the fact that $\mathbf{x} = \mathbf{x}_U + \mathbf{x}_{U^\perp}$ (by Corollary 6.5.3); so, either one of \mathbf{x}_U and \mathbf{x}_{U^\perp} can be obtained from the other by reflecting about the origin.



- Reminder: $H(\mathbf{a}) := I_n - \frac{2}{\mathbf{a}^T \mathbf{a}} \mathbf{a} \mathbf{a}^T = I_n - \frac{2}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T$.

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- So, for any $\mathbf{x} \in \mathbb{R}^n$, then the projection of \mathbf{x} onto L is given by $\mathbf{x}_L = \frac{1}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T \mathbf{x}$,

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$$\begin{aligned} \text{ref}_L(\mathbf{x}) &= 2\mathbf{x}_L - \mathbf{x} = \frac{2}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T \mathbf{x} - I_n \mathbf{x} \\ &= \left(\frac{2}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T - I_n \right) \mathbf{x} = -H(\mathbf{a}) \mathbf{x}, \end{aligned}$$

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and the reflection of \mathbf{x} about L^\perp is given by

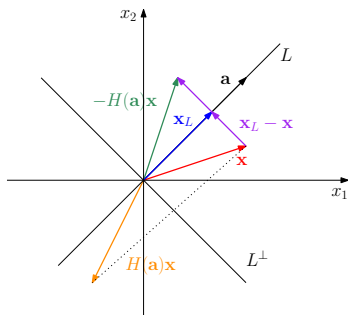
$$\text{ref}_{L^\perp}(\mathbf{x}) = -\text{ref}_L(\mathbf{x}) = H(\mathbf{a}) \mathbf{x}.$$

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- So, for any $\mathbf{x} \in \mathbb{R}^n$, then the projection of \mathbf{x} onto L is given by $\mathbf{x}_L = \frac{1}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T \mathbf{x}$, the reflection of \mathbf{x} about the line L is given by

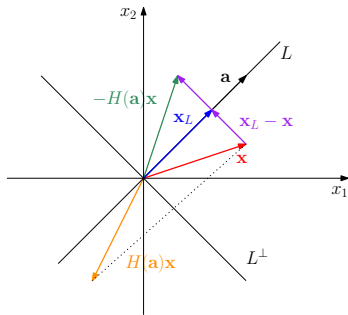
$$\begin{aligned} \text{ref}_L(\mathbf{x}) &= 2\mathbf{x}_L - \mathbf{x} = \frac{2}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T \mathbf{x} - I_n \mathbf{x} \\ &= \left(\frac{2}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T - I_n \right) \mathbf{x} = -H(\mathbf{a}) \mathbf{x}, \end{aligned}$$

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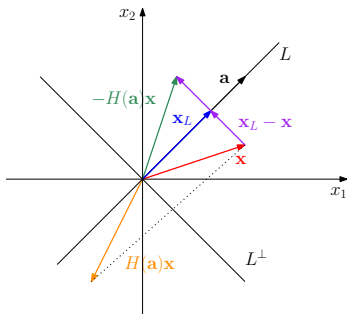


- Reminder: $H(\mathbf{a}) := I_n - \frac{2}{\mathbf{a}^T \mathbf{a}} \mathbf{a} \mathbf{a}^T = I_n - \frac{2}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T$.



- Thus, $-\mathbf{H}(\mathbf{a})$ is the standard matrix of reflection about the line $L = \text{Span}(\mathbf{a})$, whereas the Householder matrix $\mathbf{H}(\mathbf{a})$ itself is the standard matrix of reflection about L^\perp . Thus, $-\mathbf{H}(\mathbf{a})$ is the standard matrix of reflection about the $\text{Span}(\mathbf{a})$ line.

- Reminder: $H(\mathbf{a}) := I_n - \frac{2}{\mathbf{a}^T \mathbf{a}} \mathbf{a} \mathbf{a}^T = I_n - \frac{2}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T$.



- **Remark:** Suppose that \mathbf{a} is a non-zero vector in \mathbb{R}^n .
 - Then the standard matrix of reflection about the line $L := \text{Span}(\mathbf{a})$ in \mathbb{R}^n is an orthogonal matrix.
 - Indeed, as we saw, the Householder matrix $H(\mathbf{a})$ is an orthogonal matrix.
 - By Proposition 6.8.2(c), it follows that $-H(\mathbf{a})$ is also an orthogonal matrix, and as we saw above, $-H(\mathbf{a})$ is the standard matrix of reflection about the line $L = \text{Span}(\mathbf{a})$ in \mathbb{R}^n .

- Let us now give a geometric interpretation of this matrix.

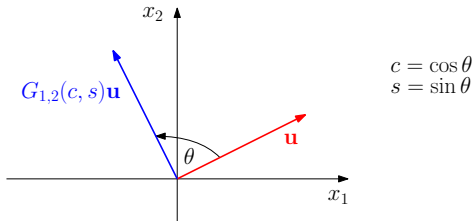
- Let us now give a geometric interpretation of this matrix.
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- Since $c^2 + s^2 = 1$, we see that there exists a real number (angle in radians) θ such that $c = \cos \theta$ and $s = \sin \theta$.
- With this set-up, we see that $G_{i,j}(c, s)$ represents rotation about the origin by angle θ in the $x_i x_j$ -plane.
- This is particularly easy to see in the case when $n = 2$. In that case, we have that

$$G_{1,2}(c, s) = \begin{bmatrix} c & -s \\ s & c \end{bmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix},$$

which is precisely the standard matrix of counterclockwise rotation about the origin by angle θ .



Theorem 6.8.5

Let $Q = [q_{i,j}]_{n \times n}$ be an orthogonal matrix in $\mathbb{R}^{n \times n}$. Then:

- Ⓐ for all $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, $(Q\mathbf{x}) \cdot (Q\mathbf{y}) = \mathbf{x} \cdot \mathbf{y}$;
- Ⓑ for all $\mathbf{x} \in \mathbb{R}^n$, $\|Q\mathbf{x}\| = \|\mathbf{x}\|$;
- Ⓒ for all $i, j \in \{1, \dots, n\}$, $|q_{i,j}| \leq 1$.

- Proof: next slide.

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- **Remark:** By Theorem 6.8.5(b), multiplication by an orthogonal matrix (on the left) preserves vector length.

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- Proof: next slide.
- **Remark:** By Theorem 6.8.5(b), multiplication by an orthogonal matrix (on the left) preserves vector length.
 - On the other hand, recall that for non-zero vectors $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, we have that $\mathbf{x} \cdot \mathbf{y} = \|\mathbf{x}\| \|\mathbf{y}\| \cos \theta$, where θ is the angle between \mathbf{x} and \mathbf{y} .

Theorem 6.8.5

Let $Q = [q_{i,j}]_{n \times n}$ be an orthogonal matrix in $\mathbb{R}^{n \times n}$. Then:

- (a) for all $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, $(Q\mathbf{x}) \cdot (Q\mathbf{y}) = \mathbf{x} \cdot \mathbf{y}$;
- (b) for all $\mathbf{x} \in \mathbb{R}^n$, $\|Q\mathbf{x}\| = \|\mathbf{x}\|$;
- (c) for all $i, j \in \{1, \dots, n\}$, $|q_{i,j}| \leq 1$.

- Proof: next slide.
- **Remark:** By Theorem 6.8.5(b), multiplication by an orthogonal matrix (on the left) preserves vector length.
 - On the other hand, recall that for non-zero vectors $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, we have that $\mathbf{x} \cdot \mathbf{y} = \|\mathbf{x}\| \|\mathbf{y}\| \cos \theta$, where θ is the angle between \mathbf{x} and \mathbf{y} .
 - So, Theorem 6.8.5(a-b) implies that multiplication (on the left) by an orthogonal matrix preserves angles between non-zero vectors.

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Proof.

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Proof. (a) For $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$, we have the following:

$$(Q\mathbf{x}) \cdot (Q\mathbf{y}) = (Q\mathbf{x})^T(Q\mathbf{y}) = \mathbf{x}^T \underbrace{Q^T Q}_{=I_n} \mathbf{y} = \mathbf{x}^T \mathbf{y} = \mathbf{x} \cdot \mathbf{y}.$$

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(b) For $\mathbf{x} \in \mathbb{R}^n$, we have the following:

$$\|Q\mathbf{x}\| = \sqrt{(Q\mathbf{x}) \cdot (Q\mathbf{x})} \stackrel{(a)}{=} \sqrt{\mathbf{x} \cdot \mathbf{x}} = \|\mathbf{x}\|.$$

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$$\|Q\mathbf{x}\| = \sqrt{(Q\mathbf{x}) \cdot (Q\mathbf{x})} \stackrel{(a)}{=} \sqrt{\mathbf{x} \cdot \mathbf{x}} = \|\mathbf{x}\|.$$

(c) By Theorem 6.8.1, the columns of Q form an orthonormal basis. In particular, all columns of Q are unit vectors, and it follows that all entries of Q have absolute value at most 1. \square

- ③ Scalar product, coordinate vectors, and matrices of linear functions

- ③ Scalar product, coordinate vectors, and matrices of linear functions

Proposition 6.9.1

Let V be a real or complex vector space, equipped with the scalar product $\langle \cdot, \cdot \rangle$ and the induced norm $\| \cdot \|$, and let $\mathcal{B} = \{\mathbf{u}_1, \dots, \mathbf{u}_n\}$ be an **orthonormal** basis of V . Let \cdot be the standard scalar product in \mathbb{R}^n or \mathbb{C}^n (depending on whether the vector space V is real or complex). Then for all $\mathbf{x}, \mathbf{y} \in V$, we have that

$$\langle \mathbf{x}, \mathbf{y} \rangle = \left[\mathbf{x} \right]_{\mathcal{B}} \cdot \left[\mathbf{y} \right]_{\mathcal{B}}.$$

- Proof: Lecture Notes.

Theorem 6.9.2

Let U and V be non-trivial, finite-dimensional **real** vector spaces. Assume that U is equipped with a scalar product $\langle \cdot, \cdot \rangle_U$ and the induced norm $\| \cdot \|_U$, and that V is equipped with a scalar product $\langle \cdot, \cdot \rangle_V$ and the induced norm $\| \cdot \|_V$. Let $\mathcal{B}_U = \{\mathbf{u}_1, \dots, \mathbf{u}_m\}$ and $\mathcal{B}_V = \{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ be **orthonormal** bases of U and V , respectively, and let $f : U \rightarrow V$ be a linear function. Then the following two statements are equivalent:

- (i) the columns of the $n \times m$ matrix ${}_{\mathcal{B}_V} [f]_{\mathcal{B}_U}$ form an orthonormal set of vectors in \mathbb{R}^n (with respect to the standard scalar product \cdot and the induced norm $\| \cdot \|$);^a
- (ii) f preserves the scalar product, that is, for all vectors $\mathbf{x}, \mathbf{y} \in U$, we have that $\langle f(\mathbf{x}), f(\mathbf{y}) \rangle_V = \langle \mathbf{x}, \mathbf{y} \rangle_U$.

^aHowever, despite Theorem 6.8.1, this does not necessarily mean that the matrix ${}_{\mathcal{B}_V} [f]_{\mathcal{B}_U}$ is orthogonal. This is because ${}_{\mathcal{B}_V} [f]_{\mathcal{B}_U}$ is an $n \times m$ matrix, and it is possible that $m \neq n$, in which case ${}_{\mathcal{B}_V} [f]_{\mathcal{B}_U}$ is not a square matrix. Only square matrices can be orthogonal!

Proof. Set ${}_{B_V} [f]_{B_U} = [\mathbf{c}_1 \quad \dots \quad \mathbf{c}_m]$.

Proof. Set ${}_{B_V} [f]_{B_U} = [\mathbf{c}_1 \quad \dots \quad \mathbf{c}_m]$. We observe that

$$\begin{aligned} ({}_{B_V} [f]_{B_U})^T {}_{B_V} [f]_{B_U} &= \begin{bmatrix} \mathbf{c}_1^T \\ \mathbf{c}_2^T \\ \vdots \\ \mathbf{c}_m^T \end{bmatrix} [\mathbf{c}_1 \quad \mathbf{c}_2 \quad \dots \quad \mathbf{c}_m] \\ &= \begin{bmatrix} \mathbf{c}_1 \cdot \mathbf{c}_1 & \mathbf{c}_1 \cdot \mathbf{c}_2 & \dots & \mathbf{c}_1 \cdot \mathbf{c}_m \\ \mathbf{c}_2 \cdot \mathbf{c}_1 & \mathbf{c}_2 \cdot \mathbf{c}_2 & \dots & \mathbf{c}_2 \cdot \mathbf{c}_m \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{c}_m \cdot \mathbf{c}_1 & \mathbf{c}_m \cdot \mathbf{c}_2 & \dots & \mathbf{c}_m \cdot \mathbf{c}_m \end{bmatrix}. \end{aligned}$$

So, we see that (i) holds iff $({}_{B_V} [f]_{B_U})^T {}_{B_V} [f]_{B_U} = I_m$.

Proof (cont.). Reminder: (i) holds iff $({}_{\mathcal{B}_V} [f]_{\mathcal{B}_U})^T {}_{\mathcal{B}_V} [f]_{\mathcal{B}_U} = I_m$.

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Next, by Proposition 6.9.1, the following hold for all $\mathbf{x}, \mathbf{y} \in U$:

(1) $\langle \mathbf{x}, \mathbf{y} \rangle_U = [\mathbf{x}]_{\mathcal{B}_U} \cdot [\mathbf{y}]_{\mathcal{B}_U}$;

(2) $\langle f(\mathbf{x}), f(\mathbf{y}) \rangle_V = [f(\mathbf{x})]_{\mathcal{B}_V} \cdot [f(\mathbf{y})]_{\mathcal{B}_V}$.

Proof (cont.). Reminder: (i) holds iff $({}_{\mathcal{B}_V} [f]_{\mathcal{B}_U})^T {}_{\mathcal{B}_V} [f]_{\mathcal{B}_U} = I_m$.

Next, by Proposition 6.9.1, the following hold for all $\mathbf{x}, \mathbf{y} \in U$:

$$(1) \langle \mathbf{x}, \mathbf{y} \rangle_U = [\mathbf{x}]_{\mathcal{B}_U} \cdot [\mathbf{y}]_{\mathcal{B}_U};$$

$$(2) \langle f(\mathbf{x}), f(\mathbf{y}) \rangle_V = [f(\mathbf{x})]_{\mathcal{B}_V} \cdot [f(\mathbf{y})]_{\mathcal{B}_V}.$$

Now, for all $\mathbf{x}, \mathbf{y} \in U$, we have that

$$\begin{aligned} \langle f(\mathbf{x}), f(\mathbf{y}) \rangle_V &\stackrel{(2)}{=} [f(\mathbf{x})]_{\mathcal{B}_V} \cdot [f(\mathbf{y})]_{\mathcal{B}_V} \\ &= ([f(\mathbf{x})]_{\mathcal{B}_V})^T [f(\mathbf{y})]_{\mathcal{B}_V} \\ &= \left({}_{\mathcal{B}_V} [f]_{\mathcal{B}_U} [\mathbf{x}]_{\mathcal{B}_U} \right)^T \left({}_{\mathcal{B}_V} [f]_{\mathcal{B}_U} [\mathbf{y}]_{\mathcal{B}_U} \right) \\ &= ([\mathbf{x}]_{\mathcal{B}_U})^T ({}_{\mathcal{B}_V} [f]_{\mathcal{B}_U})^T {}_{\mathcal{B}_V} [f]_{\mathcal{B}_U} [\mathbf{y}]_{\mathcal{B}_U}. \end{aligned}$$

Proof (continued). Suppose first that (i) holds. Then $({}_{\mathcal{B}_V} [f]_{\mathcal{B}_U})^T {}_{\mathcal{B}_V} [f]_{\mathcal{B}_U} = I_m$, and consequently, for all $\mathbf{x}, \mathbf{y} \in U$, we have that

$$\begin{aligned} \langle f(\mathbf{x}), f(\mathbf{y}) \rangle_V &= ([\mathbf{x}]_{\mathcal{B}_U})^T \underbrace{ ({}_{\mathcal{B}_V} [f]_{\mathcal{B}_U})^T {}_{\mathcal{B}_V} [f]_{\mathcal{B}_U} }_{=I_m} [\mathbf{y}]_{\mathcal{B}_U} \\ &= ([\mathbf{x}]_{\mathcal{B}_U})^T [\mathbf{y}]_{\mathcal{B}_U} \\ &= [\mathbf{x}]_{\mathcal{B}_U} \cdot [\mathbf{y}]_{\mathcal{B}_U} \\ &\stackrel{(1)}{=} \langle \mathbf{x}, \mathbf{y} \rangle_U. \end{aligned}$$

Thus, (ii) holds.

Proof (continued). Reminder: ${}_{B_V} [f]_{B_U} = [\mathbf{c}_1 \ \dots \ \mathbf{c}_m]$

Suppose now that (ii) holds. Then for all $i, j \in \{1, \dots, m\}$, we have that

$$\begin{aligned} \mathbf{e}_i^m \cdot \mathbf{e}_j^m &= [\mathbf{u}_i]_{B_U} \cdot [\mathbf{u}_j]_{B_U} \\ &\stackrel{(1)}{=} \langle \mathbf{u}_i, \mathbf{u}_j \rangle_U \\ &\stackrel{(ii)}{=} \langle f(\mathbf{u}_i), f(\mathbf{u}_j) \rangle_V \\ &\stackrel{(2)}{=} [f(\mathbf{u}_i)]_{B_V} \cdot [f(\mathbf{u}_j)]_{B_V} \\ &= ({}_{B_V} [f]_{B_U} [\mathbf{u}_i]_{B_U}) \cdot ({}_{B_V} [f]_{B_U} [\mathbf{u}_j]_{B_U}) \\ &= ({}_{B_V} [f]_{B_U} \mathbf{e}_i^m) \cdot ({}_{B_V} [f]_{B_U} \mathbf{e}_j^m) \\ &= \mathbf{c}_i \cdot \mathbf{c}_j. \end{aligned}$$

So, $\{\mathbf{c}_1, \dots, \mathbf{c}_n\}$ is an orthonormal set of vectors in \mathbb{R}^n , that is, (i) holds. \square

Theorem 6.9.2

Let U and V be non-trivial, finite-dimensional **real** vector spaces. Assume that U is equipped with a scalar product $\langle \cdot, \cdot \rangle_U$ and the induced norm $\| \cdot \|_U$, and that V is equipped with a scalar product $\langle \cdot, \cdot \rangle_V$ and the induced norm $\| \cdot \|_V$. Let $\mathcal{B}_U = \{\mathbf{u}_1, \dots, \mathbf{u}_m\}$ and $\mathcal{B}_V = \{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ be **orthonormal** bases of U and V , respectively, and let $f : U \rightarrow V$ be a linear function. Then the following two statements are equivalent:

- (i) the columns of the $n \times m$ matrix ${}_{\mathcal{B}_V} [f]_{\mathcal{B}_U}$ form an orthonormal set of vectors in \mathbb{R}^n (with respect to the standard scalar product \cdot and the induced norm $\| \cdot \|$);^a
- (ii) f preserves the scalar product, that is, for all vectors $\mathbf{x}, \mathbf{y} \in U$, we have that $\langle f(\mathbf{x}), f(\mathbf{y}) \rangle_V = \langle \mathbf{x}, \mathbf{y} \rangle_U$.

^aHowever, despite Theorem 6.8.1, this does not necessarily mean that the matrix ${}_{\mathcal{B}_V} [f]_{\mathcal{B}_U}$ is orthogonal. This is because ${}_{\mathcal{B}_V} [f]_{\mathcal{B}_U}$ is an $n \times m$ matrix, and it is possible that $m \neq n$, in which case ${}_{\mathcal{B}_V} [f]_{\mathcal{B}_U}$ is not a square matrix. Only square matrices can be orthogonal!