

LINEAR ALGEBRA with Applications

Open Edition



ADAPTABLE | ACCESSIBLE | AFFORDABLE

Adapted for

Emory University

Math 221

Linear Algebra

Sections 1 & 2 Lectured and adapted by

Le Chen

April 15, 2021

le.chen@emory.edu
Course page
http://math.emory.edu/~lchen41/teaching/2021_Spring_Math221

by W. Keith Nicholson Creative Commons License (CC BY-NC-SA)

Contents

1	Systems of Linear Equations				
	1.1	Solutions and Elementary Operations	6		
	1.2	Gaussian Elimination	16		
	1.3	Homogeneous Equations	28		
	Sup	plementary Exercises for Chapter 1	37		
2	Ma	trix Algebra	39		
	2.1	Matrix Addition, Scalar Multiplication, and Transposition	40		
	2.2	Matrix-Vector Multiplication	53		
	2.3	Matrix Multiplication	72		
	2.4	Matrix Inverses	91		
	2.5	Elementary Matrices	109		
	2.6	Linear Transformations	119		
	2.7	LU-Factorization	135		
3	Determinants and Diagonalization				
	3.1	The Cofactor Expansion	148		
	3.2	Determinants and Matrix Inverses	163		
	3.3	Diagonalization and Eigenvalues	178		
	Sup	plementary Exercises for Chapter 3	201		
4	Vec	tor Geometry	203		
	4.1	Vectors and Lines	204		
	4.2	Projections and Planes	223		
	4.3	More on the Cross Product	244		
	4.4	Linear Operators on \mathbb{R}^3	251		
	Sup	plementary Exercises for Chapter 4	260		
5	Vector Space \mathbb{R}^n 20				
	5.1	Subspaces and Spanning	264		
	5.2	Independence and Dimension	273		
	5.3	Orthogonality	287		
	5.4	Rank of a Matrix	297		

$4 \equiv \text{CONTENTS}$

	5.5	Similarity and Diagonalization)7
	Supp	plementary Exercises for Chapter 5	20
6	Vec	tor Spaces 32	!1
	6.1	Examples and Basic Properties	22
	6.2	Subspaces and Spanning Sets	33
	6.3	Linear Independence and Dimension	12
	6.4	Finite Dimensional Spaces	54
	Supp	plementary Exercises for Chapter $6 \ldots 36$	34
7	Line	ear Transformations 36	65
	7.1	Examples and Elementary Properties	36
	7.2	Kernel and Image of a Linear Transformation	74
	7.3	Isomorphisms and Composition	35
8	Ort	hogonality 39	9
	8.1	Orthogonal Complements and Projections)()
	8.2	Orthogonal Diagonalization	10
	8.3	Positive Definite Matrices	21
	8.4	QR-Factorization	27
	8.5	Computing Eigenvalues	31
	8.6	The Singular Value Decomposition	36
		8.6.1 Singular Value Decompositions	36
		8.6.2 Fundamental Subspaces	12
		8.6.3 The Polar Decomposition of a Real Square Matrix	15
		8.6.4 The Pseudoinverse of a Matrix	17

8.1 Orthogonal Complements and Projections

If $\{\mathbf{v}_1, \ldots, \mathbf{v}_m\}$ is linearly independent in a general vector space, and if \mathbf{v}_{m+1} is not in span $\{\mathbf{v}_1, \ldots, \mathbf{v}_m\}$, then $\{\mathbf{v}_1, \ldots, \mathbf{v}_m, \mathbf{v}_{m+1}\}$ is independent (Lemma 6.4.1). Here is the analog for *orthogonal* sets in \mathbb{R}^n .

Lemma 8.1.1: Orthogonal Lemma

Let $\{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_m\}$ be an orthogonal set in \mathbb{R}^n . Given \mathbf{x} in \mathbb{R}^n , write

$$\mathbf{f}_{m+1} = \mathbf{x} - \frac{\mathbf{x} \cdot \mathbf{f}_1}{\|\mathbf{f}_1\|^2} \mathbf{f}_1 - \frac{\mathbf{x} \cdot \mathbf{f}_2}{\|\mathbf{f}_2\|^2} \mathbf{f}_2 - \dots - \frac{\mathbf{x} \cdot \mathbf{f}_m}{\|\mathbf{f}_m\|^2} \mathbf{f}_m$$

Then:

1. $\mathbf{f}_{m+1} \cdot \mathbf{f}_k = 0$ for k = 1, 2, ..., m.

2. If \mathbf{x} is not in span $\{\mathbf{f}_1, \ldots, \mathbf{f}_m\}$, then $\mathbf{f}_{m+1} \neq \mathbf{0}$ and $\{\mathbf{f}_1, \ldots, \mathbf{f}_m, \mathbf{f}_{m+1}\}$ is an orthogonal set.

<u>Proof.</u> For convenience, write $t_i = (\mathbf{x} \cdot \mathbf{f}_i) / \|\mathbf{f}_i\|^2$ for each *i*. Given $1 \le k \le m$:

$$\mathbf{f}_{m+1} \cdot \mathbf{f}_k = (\mathbf{x} - t_1 \mathbf{f}_1 - \dots - t_k \mathbf{f}_k - \dots - t_m \mathbf{f}_m) \cdot \mathbf{f}_k$$

= $\mathbf{x} \cdot \mathbf{f}_k - t_1 (\mathbf{f}_1 \cdot \mathbf{f}_k) - \dots - t_k (\mathbf{f}_k \cdot \mathbf{f}_k) - \dots - t_m (\mathbf{f}_m \cdot \mathbf{f}_k)$
= $\mathbf{x} \cdot \mathbf{f}_k - t_k ||\mathbf{f}_k||^2$
= $\mathbf{0}$

This proves (1), and (2) follows because $\mathbf{f}_{m+1} \neq \mathbf{0}$ if \mathbf{x} is not in span { $\mathbf{f}_1, \ldots, \mathbf{f}_m$ }.

The orthogonal lemma has three important consequences for \mathbb{R}^n . The first is an extension for orthogonal sets of the fundamental fact that any independent set is part of a basis (Theorem 6.4.1).

Theorem 8.1.1

Let U be a subspace of \mathbb{R}^n .

1. Every orthogonal subset $\{f_1, \ldots, f_m\}$ in U is a subset of an orthogonal basis of U.

2. U has an orthogonal basis.

Proof.

1. If span $\{\mathbf{f}_1, \ldots, \mathbf{f}_m\} = U$, it is *already* a basis. Otherwise, there exists \mathbf{x} in U outside span $\{\mathbf{f}_1, \ldots, \mathbf{f}_m\}$. If \mathbf{f}_{m+1} is as given in the orthogonal lemma, then \mathbf{f}_{m+1} is in U and $\{\mathbf{f}_1, \ldots, \mathbf{f}_m, \mathbf{f}_{m+1}\}$ is orthogonal. If span $\{\mathbf{f}_1, \ldots, \mathbf{f}_m, \mathbf{f}_{m+1}\} = U$, we are done. Otherwise,

the process continues to create larger and larger orthogonal subsets of U. They are all independent by Theorem 5.3.5, so we have a basis when we reach a subset containing dim U vectors.

2. If $U = \{0\}$, the empty basis is orthogonal. Otherwise, if $\mathbf{f} \neq \mathbf{0}$ is in U, then $\{\mathbf{f}\}$ is orthogonal, so (2) follows from (1).

We can improve upon (2) of Theorem 8.1.1. In fact, the second consequence of the orthogonal lemma is a procedure by which *any* basis $\{\mathbf{x}_1, \ldots, \mathbf{x}_m\}$ of a subspace U of \mathbb{R}^n can be systematically modified to yield an orthogonal basis $\{\mathbf{f}_1, \ldots, \mathbf{f}_m\}$ of U. The \mathbf{f}_i are constructed one at a time from the \mathbf{x}_i .

To start the process, take $\mathbf{f}_1 = \mathbf{x}_1$. Then \mathbf{x}_2 is not in span $\{\mathbf{f}_1\}$ because $\{\mathbf{x}_1, \mathbf{x}_2\}$ is independent, so take

$$\mathbf{f}_2 = \mathbf{x}_2 - \frac{\mathbf{x}_2 \cdot \mathbf{f}_1}{\|\mathbf{f}_1\|^2} \mathbf{f}_1$$

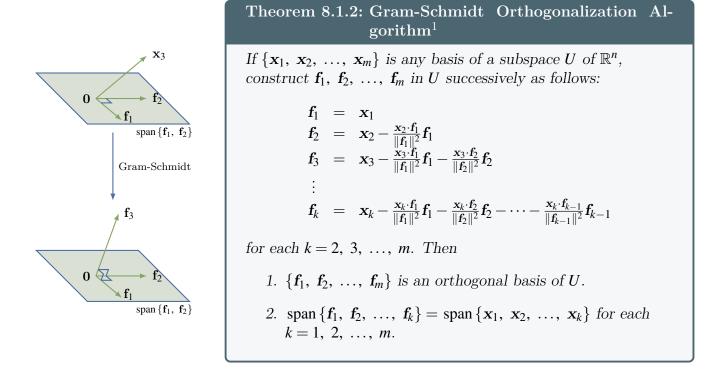
Thus $\{\mathbf{f}_1, \mathbf{f}_2\}$ is orthogonal by Lemma 8.1.1. Moreover, span $\{\mathbf{f}_1, \mathbf{f}_2\} = \text{span} \{\mathbf{x}_1, \mathbf{x}_2\}$ (verify), so \mathbf{x}_3 is not in span $\{\mathbf{f}_1, \mathbf{f}_2\}$. Hence $\{\mathbf{f}_1, \mathbf{f}_2, \mathbf{f}_3\}$ is orthogonal where

$$\mathbf{f}_3 = \mathbf{x}_3 - \frac{\mathbf{x}_3 \cdot \mathbf{f}_1}{\|\mathbf{f}_1\|^2} \mathbf{f}_1 - \frac{\mathbf{x}_3 \cdot \mathbf{f}_2}{\|\mathbf{f}_2\|^2} \mathbf{f}_2$$

Again, span { \mathbf{f}_1 , \mathbf{f}_2 , \mathbf{f}_3 } = span { \mathbf{x}_1 , \mathbf{x}_2 , \mathbf{x}_3 }, so \mathbf{x}_4 is not in span { \mathbf{f}_1 , \mathbf{f}_2 , \mathbf{f}_3 } and the process continues. At the *m*th iteration we construct an orthogonal set { \mathbf{f}_1 , ..., \mathbf{f}_m } such that

span {
$$f_1, f_2, ..., f_m$$
} = span { $x_1, x_2, ..., x_m$ } = U

Hence $\{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_m\}$ is the desired orthogonal basis of U. The procedure can be summarized as follows.



The process (for k = 3) is depicted in the diagrams. Of course, the algorithm converts any basis of \mathbb{R}^n itself into an orthogonal basis.

Example 8.1.1

Find an orthogonal basis of the row space of $A = \begin{bmatrix} 1 & 1 & -1 & -1 \\ 3 & 2 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{bmatrix}$.

<u>Solution</u>. Let \mathbf{x}_1 , \mathbf{x}_2 , \mathbf{x}_3 denote the rows of A and observe that $\{\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3\}$ is linearly independent. Take $\mathbf{f}_1 = \mathbf{x}_1$. The algorithm gives

$$\mathbf{f}_2 = \mathbf{x}_2 - \frac{\mathbf{x}_2 \cdot \mathbf{f}_1}{\|\mathbf{f}_1\|^2} \mathbf{f}_1 = (3, 2, 0, 1) - \frac{4}{4}(1, 1, -1, -1) = (2, 1, 1, 2)$$

$$\mathbf{f}_3 = \mathbf{x}_3 - \frac{\mathbf{x}_3 \cdot \mathbf{f}_1}{\|\mathbf{f}_1\|^2} \mathbf{f}_1 - \frac{\mathbf{x}_3 \cdot \mathbf{f}_2}{\|\mathbf{f}_2\|^2} \mathbf{f}_2 = \mathbf{x}_3 - \frac{0}{4} \mathbf{f}_1 - \frac{3}{10} \mathbf{f}_2 = \frac{1}{10}(4, -3, 7, -6)$$

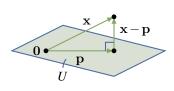
Hence $\{(1, 1, -1, -1), (2, 1, 1, 2), \frac{1}{10}(4, -3, 7, -6)\}$ is the orthogonal basis provided by the algorithm. In hand calculations it may be convenient to eliminate fractions (see the Remark below), so $\{(1, 1, -1, -1), (2, 1, 1, 2), (4, -3, 7, -6)\}$ is also an orthogonal basis for row A.

¹Erhardt Schmidt (1876–1959) was a German mathematician who studied under the great David Hilbert and later developed the theory of Hilbert spaces. He first described the present algorithm in 1907. Jörgen Pederson Gram (1850–1916) was a Danish actuary.

Remark

Observe that the vector $\frac{\mathbf{x} \cdot \mathbf{f}_i}{\|\mathbf{f}_i\|^2} \mathbf{f}_i$ is unchanged if a nonzero scalar multiple of \mathbf{f}_i is used in place of \mathbf{f}_i . Hence, if a newly constructed \mathbf{f}_i is multiplied by a nonzero scalar at some stage of the Gram-Schmidt algorithm, the subsequent \mathbf{f}_s will be unchanged. This is useful in actual calculations.

Projections



Suppose a point \mathbf{x} and a plane U through the origin in \mathbb{R}^3 are given, and we want to find the point \mathbf{p} in the plane that is closest to \mathbf{x} . Our geometric intuition assures us that such a point \mathbf{p} exists. In fact (see the diagram), \mathbf{p} must be chosen in such a way that $\mathbf{x} - \mathbf{p}$ is *perpendicular* to the plane.

Now we make two observations: first, the plane U is a *subspace* of \mathbb{R}^3 (because U contains the origin); and second, that the condition that $\mathbf{x} - \mathbf{p}$ is perpendicular to the plane U means that $\mathbf{x} - \mathbf{p}$ is orthogonal to every vector in U. In these terms the whole discussion makes sense in \mathbb{R}^n . Furthermore, the orthogonal lemma provides exactly what is needed to find \mathbf{p} in this more general setting.

Definition 8.1 Orthogonal Complement of a Subspace of \mathbb{R}^n

If U is a subspace of \mathbb{R}^n , define the **orthogonal complement** U^{\perp} of U (pronounced "U-perp") by

 $U^{\perp} = \{ \mathbf{x} \text{ in } \mathbb{R}^n \mid \mathbf{x} \cdot \mathbf{y} = 0 \text{ for all } \mathbf{y} \text{ in } U \}$

The following lemma collects some useful properties of the orthogonal complement; the proof of (1) and (2) is left as Exercise 8.1.6.

Lemma 8.1.2

Let U be a subspace of \mathbb{R}^n .

1. U^{\perp} is a subspace of \mathbb{R}^n .

2.
$$\{0\}^{\perp} = \mathbb{R}^n \text{ and } (\mathbb{R}^n)^{\perp} = \{0\}$$

3. If $U = \text{span} \{ \mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_k \}$, then $U^{\perp} = \{ \mathbf{x} \text{ in } \mathbb{R}^n \mid \mathbf{x} \cdot \mathbf{x}_i = 0 \text{ for } i = 1, 2, ..., k \}$.

Proof.

3. Let $U = \text{span} \{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_k\}$; we must show that $U^{\perp} = \{\mathbf{x} \mid \mathbf{x} \cdot \mathbf{x}_i = 0 \text{ for each } i\}$. If \mathbf{x} is in U^{\perp} then $\mathbf{x} \cdot \mathbf{x}_i = 0$ for all i because each \mathbf{x}_i is in U. Conversely, suppose that $\mathbf{x} \cdot \mathbf{x}_i = 0$ for all i; we must show that \mathbf{x} is in U^{\perp} , that is, $\mathbf{x} \cdot \mathbf{y} = 0$ for each \mathbf{y} in U. Write $\mathbf{y} = r_1 \mathbf{x}_1 + r_2 \mathbf{x}_2 + \cdots + r_k \mathbf{x}_k$, where each r_i is in \mathbb{R} . Then, using Theorem 5.3.1,

$$\mathbf{x} \cdot \mathbf{y} = r_1(\mathbf{x} \cdot \mathbf{x}_1) + r_2(\mathbf{x} \cdot \mathbf{x}_2) + \dots + r_k(\mathbf{x} \cdot \mathbf{x}_k) = r_1 \mathbf{0} + r_2 \mathbf{0} + \dots + r_k \mathbf{0} = \mathbf{0}$$

as required.

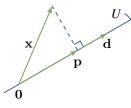
Example 8.1.2

Find U^{\perp} if $U = \text{span} \{ (1, -1, 2, 0), (1, 0, -2, 3) \}$ in \mathbb{R}^4 .

Solution. By Lemma 8.1.2, $\mathbf{x} = (x, y, z, w)$ is in U^{\perp} if and only if it is orthogonal to both (1, -1, 2, 0) and (1, 0, -2, 3); that is,

$$\begin{array}{l} x - y + 2z = 0\\ x - 2z + 3w = 0 \end{array}$$

Gaussian elimination gives $U^{\perp} = \text{span}\{(2, 4, 1, 0), (3, 3, 0, -1)\}.$



Now consider vectors \mathbf{x} and $\mathbf{d} \neq \mathbf{0}$ in \mathbb{R}^3 . The projection $\mathbf{p} = \operatorname{proj}_{\mathbf{d}} \mathbf{x}$ of \mathbf{x} on \mathbf{d} was defined in Section 4.2 as in the diagram.

The following formula for \mathbf{p} was derived in Theorem 4.2.4

$$\mathbf{p} = \operatorname{proj}_{\mathbf{d}} \mathbf{x} = \left(\frac{\mathbf{x} \cdot \mathbf{d}}{\|\mathbf{d}\|^2}\right) \mathbf{d}$$

where it is shown that $\mathbf{x} - \mathbf{p}$ is orthogonal to \mathbf{d} . Now observe that the line $U = \mathbb{R}\mathbf{d} = \{t\mathbf{d} \mid t \in \mathbb{R}\}$ is a subspace of \mathbb{R}^3 , that $\{\mathbf{d}\}$ is an bet $\mathbf{p} \in U$ and $\mathbf{x} = \mathbf{p} \in U^{\perp}$ (by Theorem 4.2.4)

orthogonal basis of U, and that $\mathbf{p} \in U$ and $\mathbf{x} - \mathbf{p} \in U^{\perp}$ (by Theorem 4.2.4).

In this form, this makes sense for any vector \mathbf{x} in \mathbb{R}^n and any subspace U of \mathbb{R}^n , so we generalize it as follows. If $\{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_m\}$ is an orthogonal basis of U, we define the projection \mathbf{p} of \mathbf{x} on Uby the formula

$$\mathbf{p} = \left(\frac{\mathbf{x} \cdot \mathbf{f}_1}{\|\mathbf{f}_1\|^2}\right) \mathbf{f}_1 + \left(\frac{\mathbf{x} \cdot \mathbf{f}_2}{\|\mathbf{f}_2\|^2}\right) \mathbf{f}_2 + \dots + \left(\frac{\mathbf{x} \cdot \mathbf{f}_m}{\|\mathbf{f}_m\|^2}\right) \mathbf{f}_m$$
(8.1)

Then $\mathbf{p} \in U$ and (by the orthogonal lemma) $\mathbf{x} - \mathbf{p} \in U^{\perp}$, so it looks like we have a generalization of Theorem 4.2.4.

However there is a potential problem: the formula (8.1) for **p** must be shown to be independent of the choice of the orthogonal basis $\{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_m\}$. To verify this, suppose that $\{\mathbf{f}'_1, \mathbf{f}'_2, \ldots, \mathbf{f}'_m\}$ is another orthogonal basis of U, and write

$$\mathbf{p}' = \left(\frac{\mathbf{x} \cdot \mathbf{f}'_1}{\|\mathbf{f}'_1\|^2}\right) \mathbf{f}'_1 + \left(\frac{\mathbf{x} \cdot \mathbf{f}'_2}{\|\mathbf{f}'_2\|^2}\right) \mathbf{f}'_2 + \dots + \left(\frac{\mathbf{x} \cdot \mathbf{f}'_m}{\|\mathbf{f}'_m\|^2}\right) \mathbf{f}'_m$$

As before, $\mathbf{p}' \in U$ and $\mathbf{x} - \mathbf{p}' \in U^{\perp}$, and we must show that $\mathbf{p}' = \mathbf{p}$. To see this, write the vector $\mathbf{p} - \mathbf{p}'$ as follows:

$$\mathbf{p} - \mathbf{p}' = (\mathbf{x} - \mathbf{p}') - (\mathbf{x} - \mathbf{p})$$

This vector is in U (because \mathbf{p} and \mathbf{p}' are in U) and it is in U^{\perp} (because $\mathbf{x} - \mathbf{p}'$ and $\mathbf{x} - \mathbf{p}$ are in U^{\perp}), and so it must be zero (it is orthogonal to itself!). This means $\mathbf{p}' = \mathbf{p}$ as desired.

Hence, the vector \mathbf{p} in equation (8.1) depends only on \mathbf{x} and the subspace U, and *not* on the choice of orthogonal basis { $\mathbf{f}_1, \ldots, \mathbf{f}_m$ } of U used to compute it. Thus, we are entitled to make the following definition:

Definition 8.2 Projection onto a Subspace of \mathbb{R}^n

Let U be a subspace of \mathbb{R}^n with orthogonal basis $\{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_m\}$. If \mathbf{x} is in \mathbb{R}^n , the vector

$$\operatorname{proj}_{U} \mathbf{x} = \frac{\mathbf{x} \cdot \mathbf{f}_{1}}{\|\mathbf{f}_{1}\|^{2}} \mathbf{f}_{1} + \frac{\mathbf{x} \cdot \mathbf{f}_{2}}{\|\mathbf{f}_{2}\|^{2}} \mathbf{f}_{2} + \dots + \frac{\mathbf{x} \cdot \mathbf{f}_{m}}{\|\mathbf{f}_{m}\|^{2}} \mathbf{f}_{m}$$

is called the **orthogonal projection** of \mathbf{x} on U. For the zero subspace $U = \{\mathbf{0}\}$, we define

 $proj_{\{0\}} x = 0$

The preceding discussion proves (1) of the following theorem.

Theorem 8.1.3: Projection Theorem

If U is a subspace of \mathbb{R}^n and x is in \mathbb{R}^n , write $\mathbf{p} = \operatorname{proj}_U \mathbf{x}$. Then:

1. **p** is in U and $\mathbf{x} - \mathbf{p}$ is in U^{\perp} .

2. \mathbf{p} is the vector in U closest to \mathbf{x} in the sense that

$$\|\mathbf{x} - \mathbf{p}\| < \|\mathbf{x} - \mathbf{y}\|$$
 for all $\mathbf{y} \in U$, $\mathbf{y} \neq \mathbf{p}$

Proof.

- 1. This is proved in the preceding discussion (it is clear if $U = \{0\}$).
- 2. Write $\mathbf{x} \mathbf{y} = (\mathbf{x} \mathbf{p}) + (\mathbf{p} \mathbf{y})$. Then $\mathbf{p} \mathbf{y}$ is in U and so is orthogonal to $\mathbf{x} \mathbf{p}$ by (1). Hence, the Pythagorean theorem gives

$$\|\mathbf{x} - \mathbf{y}\|^2 = \|\mathbf{x} - \mathbf{p}\|^2 + \|\mathbf{p} - \mathbf{y}\|^2 > \|\mathbf{x} - \mathbf{p}\|^2$$

because $\mathbf{p} - \mathbf{y} \neq \mathbf{0}$. This gives (2).

Example 8.1.3

Let $U = \text{span} \{\mathbf{x}_1, \mathbf{x}_2\}$ in \mathbb{R}^4 where $\mathbf{x}_1 = (1, 1, 0, 1)$ and $\mathbf{x}_2 = (0, 1, 1, 2)$. If $\mathbf{x} = (3, -1, 0, 2)$, find the vector in U closest to \mathbf{x} and express \mathbf{x} as the sum of a vector in U and a vector orthogonal to U.

<u>Solution</u>. { \mathbf{x}_1 , \mathbf{x}_2 } is independent but not orthogonal. The Gram-Schmidt process gives an orthogonal basis { \mathbf{f}_1 , \mathbf{f}_2 } of U where $\mathbf{f}_1 = \mathbf{x}_1 = (1, 1, 0, 1)$ and

$$\mathbf{f}_2 = \mathbf{x}_2 - \frac{\mathbf{x}_2 \cdot \mathbf{f}_1}{\|\mathbf{f}_1\|^2} \mathbf{f}_1 = \mathbf{x}_2 - \frac{3}{3} \mathbf{f}_1 = (-1, \ 0, \ 1, \ 1)$$

Hence, we can compute the projection using $\{\mathbf{f}_1, \mathbf{f}_2\}$:

$$\mathbf{p} = \operatorname{proj}_{U} \mathbf{x} = \frac{\mathbf{x} \cdot \mathbf{f}_{1}}{\|\mathbf{f}_{1}\|^{2}} \mathbf{f}_{1} + \frac{\mathbf{x} \cdot \mathbf{f}_{2}}{\|\mathbf{f}_{2}\|^{2}} \mathbf{f}_{2} = \frac{4}{3} \mathbf{f}_{1} + \frac{-1}{3} \mathbf{f}_{2} = \frac{1}{3} \begin{bmatrix} 5 & 4 & -1 & 3 \end{bmatrix}$$

Thus, **p** is the vector in U closest to **x**, and $\mathbf{x} - \mathbf{p} = \frac{1}{3}(4, -7, 1, 3)$ is orthogonal to every vector in U. (This can be verified by checking that it is orthogonal to the generators \mathbf{x}_1 and \mathbf{x}_2 of U.) The required decomposition of **x** is thus

$$\mathbf{x} = \mathbf{p} + (\mathbf{x} - \mathbf{p}) = \frac{1}{3}(5, 4, -1, 3) + \frac{1}{3}(4, -7, 1, 3)$$

Example 8.1.4

Find the point in the plane with equation 2x + y - z = 0 that is closest to the point (2, -1, -3).

<u>Solution</u>. We write \mathbb{R}^3 as rows. The plane is the subspace U whose points (x, y, z) satisfy z = 2x + y. Hence

$$U = \{(s, t, 2s+t) \mid s, t \text{ in } \mathbb{R}\} = \text{span}\{(0, 1, 1), (1, 0, 2)\}$$

The Gram-Schmidt process produces an orthogonal basis $\{\mathbf{f}_1, \mathbf{f}_2\}$ of U where $\mathbf{f}_1 = (0, 1, 1)$ and $\mathbf{f}_2 = (1, -1, 1)$. Hence, the vector in U closest to $\mathbf{x} = (2, -1, -3)$ is

$$\operatorname{proj}_{U} \mathbf{x} = \frac{\mathbf{x} \cdot \mathbf{f}_{1}}{\|\mathbf{f}_{1}\|^{2}} \mathbf{f}_{1} + \frac{\mathbf{x} \cdot \mathbf{f}_{2}}{\|\mathbf{f}_{2}\|^{2}} \mathbf{f}_{2} = -2\mathbf{f}_{1} + 0\mathbf{f}_{2} = (0, -2, -2)$$

Thus, the point in U closest to (2, -1, -3) is (0, -2, -2).

The next theorem shows that projection on a subspace of \mathbb{R}^n is actually a linear operator $\mathbb{R}^n \to \mathbb{R}^n$.

Theorem 8.1.4

Let U be a fixed subspace of \mathbb{R}^n . If we define $T : \mathbb{R}^n \to \mathbb{R}^n$ by

 $T(\mathbf{x}) = \operatorname{proj}_{U} \mathbf{x}$ for all \mathbf{x} in \mathbb{R}^{n}

- 1. T is a linear operator.
- 2. im T = U and ker $T = U^{\perp}$.
- 3. dim $U + \dim U^{\perp} = n$.

Proof. If $U = \{0\}$, then $U^{\perp} = \mathbb{R}^n$, and so $T(\mathbf{x}) = \operatorname{proj}_{\{0\}} \mathbf{x} = \mathbf{0}$ for all \mathbf{x} . Thus T = 0 is the zero (linear) operator, so (1), (2), and (3) hold. Hence assume that $U \neq \{0\}$.

1. If $\{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_m\}$ is an orthonormal basis of U, then

$$T(\mathbf{x}) = (\mathbf{x} \cdot \mathbf{f}_1)\mathbf{f}_1 + (\mathbf{x} \cdot \mathbf{f}_2)\mathbf{f}_2 + \dots + (\mathbf{x} \cdot \mathbf{f}_m)\mathbf{f}_m \quad \text{for all } \mathbf{x} \text{ in } \mathbb{R}^n$$
(8.2)

by the definition of the projection. Thus T is linear because

 $(\mathbf{x} + \mathbf{y}) \cdot \mathbf{f}_i = \mathbf{x} \cdot \mathbf{f}_i + \mathbf{y} \cdot \mathbf{f}_i$ and $(r\mathbf{x}) \cdot \mathbf{f}_i = r(\mathbf{x} \cdot \mathbf{f}_i)$ for each i

- 2. We have $\operatorname{im} T \subseteq U$ by (8.2) because each \mathbf{f}_i is in U. But if \mathbf{x} is in U, then $\mathbf{x} = T(\mathbf{x})$ by (8.2) and the expansion theorem applied to the space U. This shows that $U \subseteq \operatorname{im} T$, so $\operatorname{im} T = U$. Now suppose that \mathbf{x} is in U^{\perp} . Then $\mathbf{x} \cdot \mathbf{f}_i = \mathbf{0}$ for each i (again because each \mathbf{f}_i is in U) so \mathbf{x} is in ker T by (8.2). Hence $U^{\perp} \subseteq \ker T$. On the other hand, Theorem 8.1.3 shows that $\mathbf{x} - T(\mathbf{x})$ is in U^{\perp} for all \mathbf{x} in \mathbb{R}^n , and it follows that ker $T \subseteq U^{\perp}$. Hence ker $T = U^{\perp}$, proving (2).
- 3. This follows from (1), (2), and the dimension theorem (Theorem 7.2.4).

Exercises for 8.1

Exercise 8.1.1 In each case, use the Gram-Schmidt algorithm to convert the given basis B of V into an orthogonal basis.

- a. $V = \mathbb{R}^2$, $B = \{(1, -1), (2, 1)\}$ b. $V = \mathbb{R}^2$, $B = \{(2, 1), (1, 2)\}$ c. $V = \mathbb{R}^3$, $B = \{(1, -1, 1), (1, 0, 1), (1, 1, 2)\}$
- d. $V = \mathbb{R}^3$, $B = \{(0, 1, 1), (1, 1, 1), (1, -2, 2)\}$
- b. $\{(2, 1), \frac{3}{5}(-1, 2)\}$ d. $\{(0, 1, 1), (1, 0, 0), (0, -2, 2)\}$

Exercise 8.1.2 In each case, write **x** as the sum of a vector in U and a vector in U^{\perp} .

- a. $\mathbf{x} = (1, 5, 7), U = \text{span} \{ (1, -2, 3), (-1, 1, 1) \}$
- b. $\mathbf{x} = (2, 1, 6), U = \text{span} \{ (3, -1, 2), (2, 0, -3) \}$
- c. $\mathbf{x} = (3, 1, 5, 9),$ $U = \text{span} \{ (1, 0, 1, 1), (0, 1, -1, 1), (-2, 0, 1, 1) \}$
- d. $\mathbf{x} = (2, 0, 1, 6),$ $U = \text{span} \{ (1, 1, 1, 1), (1, 1, -1, -1), (1, -1, 1, -1) \}$
- e. $\mathbf{x} = (a, b, c, d),$ $U = \text{span} \{ (1, 0, 0, 0), (0, 1, 0, 0), (0, 0, 1, 0) \}$
- f. $\mathbf{x} = (a, b, c, d),$ $U = \text{span} \{ (1, -1, 2, 0), (-1, 1, 1, 1) \}$

- b. $\mathbf{x} = \frac{1}{182}(271, -221, 1030) + \frac{1}{182}(93, 403, 62)$ d. $\mathbf{x} = \frac{1}{4}(1, 7, 11, 17) + \frac{1}{4}(7, -7, -7, 7)$
- f. $\mathbf{x} = \frac{1}{12}(5a-5b+c-3d, -5a+5b-c+3d, a-b+11c+3d, -3a+3b+3c+3d) + \frac{1}{12}(7a+5b-c+3d, 5a+7b+c-3d, -a+b+c-3d, 3a-3b-3c+9d)$

Exercise 8.1.3 Let $\mathbf{x} = (1, -2, 1, 6)$ in \mathbb{R}^4 , and let $U = \text{span} \{ (2, 1, 3, -4), (1, 2, 0, 1) \}.$

- a. Compute $\operatorname{proj}_U \mathbf{x}$.
- b. Show that $\{(1, 0, 2, -3), (4, 7, 1, 2)\}$ is another orthogonal basis of U.
- c. Use the basis in part (b) to compute $\operatorname{proj}_U \mathbf{x}$.
- a. $\frac{1}{10}(-9, 3, -21, 33) = \frac{3}{10}(-3, 1, -7, 11)$ c. $\frac{1}{70}(-63, 21, -147, 231) = \frac{3}{10}(-3, 1, -7, 11)$

Exercise 8.1.4 In each case, use the Gram-Schmidt algorithm to find an orthogonal basis of the subspace U, and find the vector in U closest to \mathbf{x} .

- a. $U = \text{span}\{(1, 1, 1), (0, 1, 1)\}, \mathbf{x} = (-1, 2, 1)$
- b. $U = \text{span} \{ (1, -1, 0), (-1, 0, 1) \}, \mathbf{x} = (2, 1, 0) \}$
- c. $U = \text{span} \{ (1, 0, 1, 0), (1, 1, 1, 0), (1, 1, 0, 0) \},\$ $\mathbf{x} = (2, 0, -1, 3)$

- d. $U = \text{span} \{ (1, -1, 0, 1), (1, 1, 0, 0), (1, 1, 0, 1) \}$, **Exercise 8.1.10** If U is a subspace of \mathbb{R}^n , show that $\mathbf{x} = (2, 0, 3, 1)$ $\operatorname{proj}_U \mathbf{x} = \mathbf{x}$ for all \mathbf{x} in U.
- b. {(1, -1, 0), $\frac{1}{2}(-1, -1, 2)$ }; proj_U **x** = (1, 0, -1)
- d. {(1, -1, 0, 1), (1, 1, 0, 0), $\frac{1}{3}(-1, 1, 0, 2)$ }; proj_U **x** = (2, 0, 0, 1)

Exercise 8.1.5 Let $U = \text{span} \{ \mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k \}$, \mathbf{v}_i in \mathbb{R}^n , and let A be the $k \times n$ matrix with the \mathbf{v}_i as rows.

- a. Show that $U^{\perp} = \{ \mathbf{x} \mid \mathbf{x} \text{ in } \mathbb{R}^n, A\mathbf{x}^T = \mathbf{0} \}.$
- b. Use part (a) to find U^{\perp} if $U = \text{span} \{ (1, -1, 2, 1), (1, 0, -1, 1) \}.$
- b. $U^{\perp} = \text{span} \{ (1, 3, 1, 0), (-1, 0, 0, 1) \}$

Exercise 8.1.6

- a. Prove part 1 of Lemma 8.1.2.
- b. Prove part 2 of Lemma 8.1.2.

Exercise 8.1.7 Let U be a subspace of \mathbb{R}^n . If \mathbf{x} in \mathbb{R}^n can be written in any way at all as $\mathbf{x} = \mathbf{p} + \mathbf{q}$ with \mathbf{p} in U and \mathbf{q} in U^{\perp} , show that necessarily $\mathbf{p} = \operatorname{proj}_U \mathbf{x}$.

Exercise 8.1.8 Let U be a subspace of \mathbb{R}^n and let \mathbf{x} be a vector in \mathbb{R}^n . Using Exercise 8.1.7, or otherwise, show that \mathbf{x} is in U if and only if $\mathbf{x} = \operatorname{proj}_U \mathbf{x}$.

Write $\mathbf{p} = \operatorname{proj}_U \mathbf{x}$. Then \mathbf{p} is in U by definition. If \mathbf{x} is U, then $\mathbf{x} - \mathbf{p}$ is in U. But $\mathbf{x} - \mathbf{p}$ is also in U^{\perp} by Theorem 8.1.3, so $\mathbf{x} - \mathbf{p}$ is in $U \cap U^{\perp} = \{\mathbf{0}\}$. Thus $\mathbf{x} = \mathbf{p}$.

Exercise 8.1.9 Let U be a subspace of \mathbb{R}^n .

- a. Show that $U^{\perp} = \mathbb{R}^n$ if and only if $U = \{0\}$.
- b. Show that $U^{\perp} = \{\mathbf{0}\}$ if and only if $U = \mathbb{R}^n$.

Exercise 8.1.10 If U is a subspace of \mathbb{R}^n , show that $\operatorname{proj}_U \mathbf{x} = \mathbf{x}$ for all \mathbf{x} in U. Let $\{\mathbf{f}_1, \mathbf{f}_2, \ldots, \mathbf{f}_m\}$ be an orthonormal basis of U. If \mathbf{x} is in U the expansion theorem gives $\mathbf{x} = (\mathbf{x} \cdot \mathbf{f}_1)\mathbf{f}_1 + (\mathbf{x} \cdot \mathbf{f}_2)\mathbf{f}_2 + \cdots + (\mathbf{x} \cdot \mathbf{f}_m)\mathbf{f}_m = \operatorname{proj}_U \mathbf{x}$.

Exercise 8.1.11 If U is a subspace of \mathbb{R}^n , show that $\mathbf{x} = \operatorname{proj}_U \mathbf{x} + \operatorname{proj}_{U^{\perp}} \mathbf{x}$ for all \mathbf{x} in \mathbb{R}^n .

Exercise 8.1.12 If $\{\mathbf{f}_1, \ldots, \mathbf{f}_n\}$ is an orthogonal basis of \mathbb{R}^n and $U = \operatorname{span} \{\mathbf{f}_1, \ldots, \mathbf{f}_m\}$, show that $U^{\perp} = \operatorname{span} \{\mathbf{f}_{m+1}, \ldots, \mathbf{f}_n\}$.

Exercise 8.1.13 If U is a subspace of \mathbb{R}^n , show that $U^{\perp\perp} = U$. [*Hint*: Show that $U \subseteq U^{\perp\perp}$, then use Theorem 8.1.4 (3) twice.]

Exercise 8.1.14 If *U* is a subspace of \mathbb{R}^n , show how to find an $n \times n$ matrix *A* such that $U = \{\mathbf{x} \mid A\mathbf{x} = \mathbf{0}\}$. [*Hint*: Exercise 8.1.13.]

Let $\{\mathbf{y}_1, \mathbf{y}_2, \dots, \mathbf{y}_m\}$ be a basis of U^{\perp} , and let A be the $n \times n$ matrix with rows $\mathbf{y}_1^T, \mathbf{y}_2^T, \dots, \mathbf{y}_m^T, 0, \dots, 0$. Then $A\mathbf{x} = \mathbf{0}$ if and only if $\mathbf{y}_i \cdot \mathbf{x} = 0$ for each $i = 1, 2, \dots, m$; if and only if \mathbf{x} is in $U^{\perp \perp} = U$.

Exercise 8.1.15 Write \mathbb{R}^n as rows. If A is an $n \times n$ matrix, write its null space as null $A = \{\mathbf{x} \text{ in } \mathbb{R}^n \mid A\mathbf{x}^T = \mathbf{0}\}$. Show that:

a) null
$$A = (\operatorname{row} A)^{\perp}$$
; b) null $A^T = (\operatorname{col} A)^{\perp}$.

Exercise 8.1.16 If U and W are subspaces, show that $(U+W)^{\perp} = U^{\perp} \cap W^{\perp}$. [See Exercise 5.1.22.]

Exercise 8.1.17 Think of \mathbb{R}^n as consisting of rows.

- a. Let *E* be an $n \times n$ matrix, and let $U = \{ \mathbf{x}E \mid \mathbf{x} \text{ in } \mathbb{R}^n \}$. Show that the following are equivalent.
 - i. $E^2 = E = E^T$ (*E* is a **projection matrix**).
 - ii. $(\mathbf{x} \mathbf{x}E) \cdot (\mathbf{y}E) = 0$ for all \mathbf{x} and \mathbf{y} in \mathbb{R}^n .
 - iii. $\operatorname{proj}_U \mathbf{x} = \mathbf{x}E$ for all \mathbf{x} in \mathbb{R}^n . [*Hint*: For (ii) implies (iii): Write $\mathbf{x} = \mathbf{x}E + (\mathbf{x} - \mathbf{x}E)$ and use the uniqueness argument preceding the definition of $\operatorname{proj}_U \mathbf{x}$. For (iii) implies (ii): $\mathbf{x} - \mathbf{x}E$ is in U^{\perp} for all \mathbf{x} in \mathbb{R}^n .]
- b. If E is a projection matrix, show that I E is also a projection matrix.

- matrices, show that E + F is also a projection matrix.
- d. If A is $m \times n$ and AA^T is invertible, show that $E = A^T (AA^T)^{-1}A$ is a projection matrix.

d.
$$E^T = A^T [(AA^T)^{-1}]^T (A^T)^T = A^T [(AA^T)^T]^{-1}A = A^T [AA^T]^{-1}A = E E^2 = A^T (AA^T)^{-1}AA^T (AA^T)^{-1}A = A^T (AA^T)^{-1}A = E$$

Exercise 8.1.18 Let *A* be an $n \times n$ matrix of rank r. Show that there is an invertible $n \times n$ matrix U such that UA is a row-echelon matrix with the property that the first r rows are orthogonal. [*Hint*: Let R be the row-echelon form of A, and use the Gram-Schmidt process on the nonzero rows of R from the bottom up. Use Lemma 2.4.1.]

Exercise 8.1.19 Let A be an $(n-1) \times n$ matrix with rows $\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_{n-1}$ and let A_i denote the

c. If EF = 0 = FE and E and F are projection $(n-1) \times (n-1)$ matrix obtained from A by deleting column *i*. Define the vector \mathbf{y} in \mathbb{R}^n by

$$\mathbf{y} = \left[\det A_1 - \det A_2 \, \det A_3 \, \cdots \, (-1)^{n+1} \det A_n \right]$$

Show that:

a.
$$\mathbf{x}_i \cdot \mathbf{y} = 0$$
 for all $i = 1, 2, ..., n-1$. [*Hint*:
Write $B_i = \begin{bmatrix} x_i \\ A \end{bmatrix}$ and show that det $B_i = 0$.]

- b. $\mathbf{y} \neq \mathbf{0}$ if and only if $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_{n-1}\}$ is linearly independent. [*Hint*: If some det $A_i \neq 0$, the rows of A_i are linearly independent. Conversely, if the \mathbf{x}_i are independent, consider A = UR where R is in reduced row-echelon form.]
- c. If $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_{n-1}\}$ is linearly independent, use Theorem 8.1.3(3) to show that all solutions to the system of n-1 homogeneous equations

 $A\mathbf{x}^T = \mathbf{0}$

are given by $t\mathbf{y}$, t a parameter.