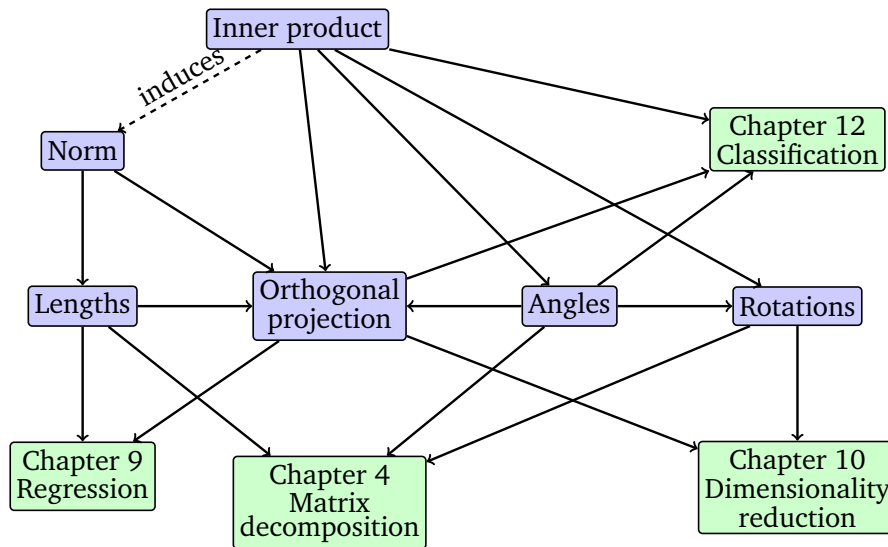


Analytic Geometry

1464 In Chapter 2, we studied vectors, vector spaces and linear mappings at
 1465 a general but abstract level. In this chapter, we will add some geometric
 1466 interpretation and intuition to all of these concepts. In particular, we will
 1467 look at geometric vectors, compute their lengths and distances or angles
 1468 between two vectors. To be able to do this, we equip the vector space with
 1469 an inner product that induces the geometry of the vector space. Inner
 1470 products and their corresponding norms and metrics capture the intuitive
 1471 notions of similarity and distances, which we use to develop the Support
 1472 Vector Machine in Chapter 12. We will then use the concepts of lengths
 1473 and angles between vectors to discuss orthogonal projections, which will
 1474 play a central role when we discuss principal component analysis in Chap-
 1475 ter 10 and regression via maximum likelihood estimation in Chapter 9.
 1476 Figure 3.1 gives an overview of how concepts in this chapter are related
 1477 and how they are connected to other chapters of the book.

Figure 3.1 A mind map of the concepts introduced in this chapter, along with when they are used in other parts of the book.



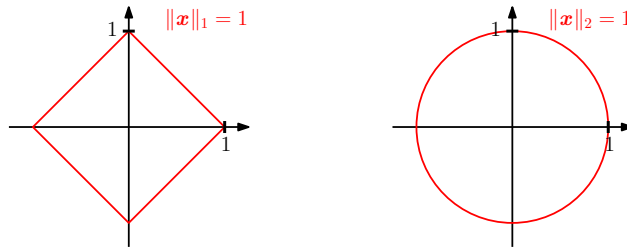


Figure 3.3 For different norms, the red lines indicate the set of vectors with norm 1. Left: Manhattan distance; Right: Euclidean distance.

3.1 Norms

When we think of geometric vectors, i.e., directed line segments that start at the origin, then intuitively the length of a vector is the distance of the “end” of this directed line segment from the origin. In the following, we will discuss the notion of the length of vectors using the concept of a norm.

Definition 3.1 (Norm). A norm on a vector space V is a function

norm

$$\|\cdot\| : V \rightarrow \mathbb{R}, \quad (3.1)$$

$$x \mapsto \|x\|, \quad (3.2)$$

which assigns each vector x its *length* $\|x\| \in \mathbb{R}$, such that for all $\lambda \in \mathbb{R}$ and $x, y \in V$ the following hold:

- Absolutely homogeneous: $\|\lambda x\| = |\lambda| \|x\|$
- Triangle inequality: $\|x + y\| \leq \|x\| + \|y\|$
- Positive definite: $\|x\| \geq 0$ and $\|x\| = 0 \iff x = 0$.

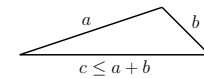
Triangle inequality

Positive definite

In geometric terms, the triangle inequality states that for any triangle, the sum of the lengths of any two sides must be greater than or equal to the length of the remaining side; see Figure 3.2 for an illustration.

Recall that for a vector $x \in \mathbb{R}^n$ we denote the elements of the vector using a subscript, that is x_i is the i^{th} element of the vector x .

Figure 3.2 Triangle inequality.



Example (Manhattan Distance)

The *Manhattan distance* on \mathbb{R}^n is defined for $x \in \mathbb{R}^n$ as

Manhattan distance

$$\|x\|_1 := \sum_{i=1}^n |x_i|, \quad (3.3)$$

where $|\cdot|$ is the absolute value. The left panel of Figure 3.3 indicates all vectors $x \in \mathbb{R}^2$ with $\|x\|_1 = 1$. The Manhattan distance is also called ℓ_1 norm.

ℓ_1 norm

Example (Euclidean Norm)

The length of a vector $\mathbf{x} \in \mathbb{R}^n$ is given by

$$\|\mathbf{x}\|_2 := \sqrt{\sum_{i=1}^n x_i^2} = \sqrt{\mathbf{x}^\top \mathbf{x}}, \quad (3.4)$$

Euclidean distance
Euclidean norm
 ℓ_2 norm

which computes the *Euclidean distance* of \mathbf{x} from the origin. This norm is called the *Euclidean norm*. The right panel of Figure 3.3 shows all vectors $\mathbf{x} \in \mathbb{R}^2$ with $\|\mathbf{x}\|_2 = 1$. The Euclidean norm is also called ℓ_2 norm.

1493 *Remark.* Throughout this book, we will use the Euclidean norm (3.4) by
1494 default if not stated otherwise. \diamond

Cauchy-Schwarz
inequality

Remark (Inner Products and Norms). Every inner product induces a norm, but there are norms (like the ℓ_1 norm) without a corresponding inner product. For an inner product vector space $(V, \langle \cdot, \cdot \rangle)$ the induced norm $\|\cdot\|$ satisfies the *Cauchy-Schwarz inequality*

$$|\langle \mathbf{x}, \mathbf{y} \rangle| \leq \|\mathbf{x}\| \|\mathbf{y}\|. \quad (3.5)$$

1495

\diamond

3.2 Inner Products

1496

1497 Inner products allow for the introduction of intuitive geometrical con-
1498 cepts, such as the length of a vector and the angle or distance between
1499 two vectors. A major purpose of inner products is to determine whether
1500 vectors are orthogonal to each other.

3.2.1 Dot Product

1501

scalar product
dot product

We may already be familiar with a particular type of inner product, the *scalar product/dot product* in \mathbb{R}^n , which is given by

$$\mathbf{x}^\top \mathbf{y} = \sum_{i=1}^n x_i y_i. \quad (3.6)$$

1502 We will refer to the particular inner product above as the dot product
1503 in this book. However, inner products are more general concepts with
1504 specific properties, which we will now introduce.

3.2.2 General Inner Products

1505

bilinear mapping

Recall the linear mapping from Section 2.7, where we can rearrange the mapping with respect to addition and multiplication with a scalar. A *bilinear*

mapping Ω is a mapping with two arguments, and it is linear in each argument, i.e., when we look at a vector space V then it holds that for all $\mathbf{x}, \mathbf{y}, \mathbf{z} \in V, \lambda \in \mathbb{R}$

$$\Omega(\lambda \mathbf{x} + \mathbf{y}, \mathbf{z}) = \lambda \Omega(\mathbf{x}, \mathbf{z}) + \Omega(\mathbf{y}, \mathbf{z}) \quad (3.7)$$

$$\Omega(\mathbf{x}, \lambda \mathbf{y} + \mathbf{z}) = \lambda \Omega(\mathbf{x}, \mathbf{y}) + \Omega(\mathbf{x}, \mathbf{z}). \quad (3.8)$$

Equation (3.7) asserts that Ω is linear in the first argument, and equation (3.8) asserts that Ω is linear in the second argument.

Definition 3.2. Let V be a vector space and $\Omega : V \times V \rightarrow \mathbb{R}$ be a bilinear mapping that takes two vectors and maps them onto a real number. Then

- Ω is called *symmetric* if $\Omega(\mathbf{x}, \mathbf{y}) = \Omega(\mathbf{y}, \mathbf{x})$ for all $\mathbf{x}, \mathbf{y} \in V$, i.e., the order of the arguments does not matter. symmetric
- Ω is called *positive definite* if positive definite

$$\forall \mathbf{x} \in V \setminus \{\mathbf{0}\} : \Omega(\mathbf{x}, \mathbf{x}) > 0, \quad \Omega(\mathbf{0}, \mathbf{0}) = 0 \quad (3.9)$$

Definition 3.3. Let V be a vector space and $\Omega : V \times V \rightarrow \mathbb{R}$ be a bilinear mapping that takes two vectors and maps them onto a real number. Then

- A positive definite, symmetric bilinear mapping $\Omega : V \times V \rightarrow \mathbb{R}$ is called an *inner product* on V . We typically write $\langle \mathbf{x}, \mathbf{y} \rangle$ instead of $\Omega(\mathbf{x}, \mathbf{y})$. inner product
 - The pair $(V, \langle \cdot, \cdot \rangle)$ is called an *inner product space* or (real) *vector space with inner product*. If we use the dot product defined in (3.6), we call $(V, \langle \cdot, \cdot \rangle)$ a *Euclidean vector space*. inner product space
vector space with inner product
Euclidean vector space
- We will refer to the spaces above as inner product spaces in this book. space

Example (Inner Product that is not the Dot Product)

Consider $V = \mathbb{R}^2$. If we define

$$\langle \mathbf{x}, \mathbf{y} \rangle := x_1 y_1 - (x_1 y_2 + x_2 y_1) + 2x_2 y_2 \quad (3.10)$$

then $\langle \cdot, \cdot \rangle$ is an inner product but different from the dot product. The proof will be an exercise.

3.2.3 Symmetric, Positive Definite Matrices

Symmetric, positive definite (SPD) matrices play an important role in machine learning, and they are defined via the inner product.

Consider an n -dimensional vector space V with an inner product $\langle \cdot, \cdot \rangle : V \times V \rightarrow \mathbb{R}$ (see Definition 3.3) and an ordered basis $B = (\mathbf{b}_1, \dots, \mathbf{b}_n)$ of V . Recall the definition of a basis (Section 2.6.1), which says that any vector can be written as a linear combination of basis vectors. That is, for any vectors $\mathbf{x} \in V$ and $\mathbf{y} \in V$ we can write them as $\mathbf{x} = \sum_{i=1}^n \psi_i \mathbf{b}_i \in V$

and $\mathbf{y} = \sum_{j=1}^n \lambda_j \mathbf{b}_j \in V$, for $\psi_i, \lambda_j \in \mathbb{R}$. Due to the bilinearity of the inner product it holds that for all \mathbf{x} and \mathbf{y} that

$$\langle \mathbf{x}, \mathbf{y} \rangle = \left\langle \sum_{i=1}^n \psi_i \mathbf{b}_i, \sum_{j=1}^n \lambda_j \mathbf{b}_j \right\rangle = \sum_{i=1}^n \sum_{j=1}^n \psi_i \langle \mathbf{b}_i, \mathbf{b}_j \rangle \lambda_j = \hat{\mathbf{x}}^\top \mathbf{A} \hat{\mathbf{y}}, \quad (3.11)$$

where $A_{ij} := \langle \mathbf{b}_i, \mathbf{b}_j \rangle$ and $\hat{\mathbf{x}}, \hat{\mathbf{y}}$ are the coordinates of \mathbf{x} and \mathbf{y} with respect to the basis B . This implies that the inner product $\langle \cdot, \cdot \rangle$ is uniquely determined through \mathbf{A} . The symmetry of the inner product also means that \mathbf{A} is symmetric. Furthermore, the positive definiteness of the inner product implies that

$$\forall \mathbf{x} \in V \setminus \{\mathbf{0}\} : \mathbf{x}^\top \mathbf{A} \mathbf{x} > 0. \quad (3.12)$$

positive definite

A symmetric matrix \mathbf{A} that satisfies (3.12) is called *positive definite*.

Example (SPD Matrices)

Consider the following matrices:

$$\mathbf{A}_1 = \begin{bmatrix} 9 & 6 \\ 6 & 5 \end{bmatrix}, \quad \mathbf{A}_2 = \begin{bmatrix} 9 & 6 \\ 6 & 3 \end{bmatrix} \quad (3.13)$$

Then, \mathbf{A}_1 is positive definite because it is symmetric and

$$\mathbf{x}^\top \mathbf{A}_1 \mathbf{x} = \begin{bmatrix} x_1 & x_2 \end{bmatrix} \begin{bmatrix} 9 & 6 \\ 6 & 5 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \quad (3.14)$$

$$= 9x_1^2 + 12x_1x_2 + 5x_2^2 = (3x_1 + 2x_2)^2 + x_2^2 > 0 \quad (3.15)$$

for all $\mathbf{x} \in V \setminus \{\mathbf{0}\}$. However, \mathbf{A}_2 is symmetric but not positive definite because $\mathbf{x}^\top \mathbf{A}_2 \mathbf{x} = 9x_1^2 + 12x_1x_2 + 3x_2^2 = (3x_1 + 2x_2)^2 - x_2^2$ can be smaller than 0, e.g., for $\mathbf{x} = [2, -3]^\top$.

If $\mathbf{A} \in \mathbb{R}^{n \times n}$ is symmetric, positive definite then

$$\langle \mathbf{x}, \mathbf{y} \rangle = \hat{\mathbf{x}}^\top \mathbf{A} \hat{\mathbf{y}} \quad (3.16)$$

1523 defines an inner product with respect to an ordered basis B where $\hat{\mathbf{x}}$ and
1524 $\hat{\mathbf{y}}$ are the coordinate representations of $\mathbf{x}, \mathbf{y} \in V$ with respect to B .

Theorem 3.4. For a real-valued, finite-dimensional vector space V and an ordered basis B of V it holds that $\langle \cdot, \cdot \rangle : V \times V \rightarrow \mathbb{R}$ is an inner product if and only if there exists a symmetric, positive definite matrix $\mathbf{A} \in \mathbb{R}^{n \times n}$ with

$$\langle \mathbf{x}, \mathbf{y} \rangle = \hat{\mathbf{x}}^\top \mathbf{A} \hat{\mathbf{y}}. \quad (3.17)$$

1525 The following properties hold if $\mathbf{A} \in \mathbb{R}^{n \times n}$ is symmetric and positive
1526 definite of order n :

- 1527 • The nullspace (kernel) of \mathbf{A} consists only of $\mathbf{0}$ because $\mathbf{x}^\top \mathbf{A} \mathbf{x} > 0$ for
1528 all $\mathbf{x} \neq \mathbf{0}$. This implies that $\mathbf{A} \mathbf{x} \neq \mathbf{0}$ if $\mathbf{x} \neq \mathbf{0}$.

- The diagonal elements of \mathbf{A} are positive because $a_{ii} = \mathbf{e}_i^\top \mathbf{A} \mathbf{e}_i > 0$, where \mathbf{e}_i is the i th vector of the standard basis in \mathbb{R}^n .

In Section 4.3, we will return to symmetric, positive definite matrices in the context of matrix decompositions.

3.3 Lengths and Distances

In Section 3.1, we already discussed norms that we can use to compute the length of a vector. Inner products and norms are closely related in the sense that any inner product induces a norm

Inner products induce norms.

$$\|\mathbf{x}\| := \sqrt{\langle \mathbf{x}, \mathbf{x} \rangle} \quad (3.18)$$

in a natural way, such that we can compute lengths of vectors using the inner product. However, not every norm is induced by an inner product. The Manhattan distance (3.3) is an example of a norm that is not induced by an inner product. In the following, we will focus on norms that are induced by inner products and introduce geometric concepts, such as lengths, distances and angles.

Example (Length of Vectors using Inner Products)

In geometry, we are often interested in lengths of vectors. We can now use an inner product to compute them using (3.18). Let us take $\mathbf{x} = [1, 1]^\top \in \mathbb{R}^2$. If we use the dot product as the inner product, with (3.18) we obtain

$$\|\mathbf{x}\| = \sqrt{\mathbf{x}^\top \mathbf{x}} = \sqrt{1^2 + 1^2} = \sqrt{2} \quad (3.19)$$

as the length of \mathbf{x} . Let us now choose a different inner product:

$$\langle \mathbf{x}, \mathbf{y} \rangle := \mathbf{x}^\top \begin{bmatrix} 1 & -\frac{1}{2} \\ -\frac{1}{2} & 1 \end{bmatrix} \mathbf{y} = x_1 y_1 - \frac{1}{2}(x_1 y_2 + x_2 y_1) + x_2 y_2. \quad (3.20)$$

If we compute the norm of a vector, then this inner product returns smaller values than the dot product if x_1 and x_2 have the same sign (and $x_1 x_2 > 0$), otherwise it returns greater values than the dot product. With this inner product we obtain

$$\langle \mathbf{x}, \mathbf{x} \rangle = x_1^2 - x_1 x_2 + x_2^2 = 1 - 1 + 1 = 1 \implies \|\mathbf{x}\| = \sqrt{1} = 1, \quad (3.21)$$

such that \mathbf{x} is “shorter” with this inner product than with the dot product.

Definition 3.5 (Distance and Metric). Consider an inner product space $(V, \langle \cdot, \cdot \rangle)$. Then

$$d(\mathbf{x}, \mathbf{y}) := \|\mathbf{x} - \mathbf{y}\| = \sqrt{\langle \mathbf{x} - \mathbf{y}, \mathbf{x} - \mathbf{y} \rangle} \quad (3.22)$$

is called *distance* of $\mathbf{x}, \mathbf{y} \in V$. If we use the dot product as the inner product, then the distance is called *Euclidean distance*. The mapping

distance
Euclidean distance

$$d : V \times V \rightarrow \mathbb{R} \quad (3.23)$$

$$(x, y) \mapsto d(x, y) \quad (3.24)$$

metric

is called *metric*.

Remark. Similar to the length of a vector, the distance between vectors does not require an inner product: a norm is sufficient. If we have a norm induced by an inner product, the distance may vary depending on the choice of the inner product. \diamond

A metric d satisfies:

positive definite

1. d is *positive definite*, i.e., $d(x, y) \geq 0$ for all $x, y \in V$ and $d(x, y) = 0 \iff x = y$

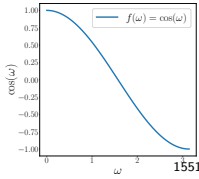
symmetric

2. d is *symmetric*, i.e., $d(x, y) = d(y, x)$ for all $x, y \in V$.

Triangular inequality

3. *Triangular inequality*: $d(x, z) \leq d(x, y) + d(y, z)$.

Figure 3.4 When restricted to $[0, \pi]$ then $f(\omega) = \cos(\omega)$ returns a unique number in the interval $[-1, 1]$.



angle

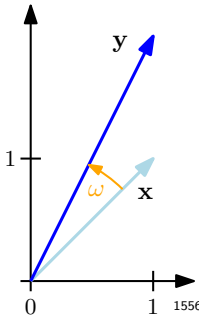
Therefore, there exists a unique $\omega \in [0, \pi]$ with

$$-1 \leq \frac{\langle x, y \rangle}{\|x\| \|y\|} \leq 1. \quad (3.25)$$

$$\cos \omega = \frac{\langle x, y \rangle}{\|x\| \|y\|}, \quad (3.26)$$

see Figure 3.4 for an illustration. The number ω is the *angle* between the vectors x and y . Intuitively, the angle between two vectors tells us how similar their orientations are. For example, using the dot product, the angle between x and $y = 4x$, i.e., y is a scaled version of x , is 0: Their orientation is the same.

Figure 3.5 The angle ω between two vectors x, y is computed using the inner product.



Example (Angle between Vectors)

Let us compute the angle between $x = [1, 1]^T \in \mathbb{R}^2$ and $y = [1, 2]^T \in \mathbb{R}^2$, see Figure 3.5, where we use the dot product as the inner product. Then we get

$$\cos \omega = \frac{\langle x, y \rangle}{\sqrt{\langle x, x \rangle \langle y, y \rangle}} = \frac{x^T y}{\sqrt{x^T x y^T y}} = \frac{3}{\sqrt{10}}, \quad (3.27)$$

and the angle between the two vectors is $\arccos(\frac{3}{\sqrt{10}}) \approx 0.32$ rad, which corresponds to about 18° .

The inner product also allows us to characterize vectors that are most dissimilar, i.e., orthogonal.

Definition 3.6 (Orthogonality). Two vectors \mathbf{x} and \mathbf{y} are *orthogonal* if and only if $\langle \mathbf{x}, \mathbf{y} \rangle = 0$, and we write $\mathbf{x} \perp \mathbf{y}$.

An implication of this definition is that the $\mathbf{0}$ -vector is orthogonal to every vector in the vector space.

Remark. Orthogonality is the generalization of the concept of perpendicularity to bilinear forms that do not have to be the dot product. In our context, geometrically, we can think of orthogonal vectors to have a right angle with respect to a specific inner product. \diamond

Example (Orthogonal Vectors)

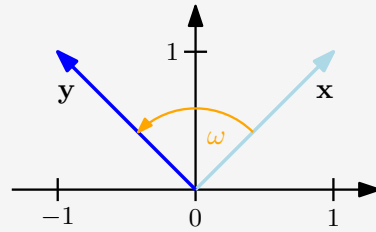


Figure 3.6 The angle ω between two vectors \mathbf{x}, \mathbf{y} can change depending on the inner product.

Consider two vectors $\mathbf{x} = [1, 1]^\top, \mathbf{y} = [-1, 1]^\top \in \mathbb{R}^2$, see Figure 3.6. We are interested in determining the angle ω between them using two different inner products. Using the dot product as inner product yields an angle ω between \mathbf{x} and \mathbf{y} of 90° , such that $\mathbf{x} \perp \mathbf{y}$. However, if we choose the inner product

$$\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^\top \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix} \mathbf{y}, \quad (3.28)$$

we get that the angle ω between \mathbf{x} and \mathbf{y} is given by

$$\cos \omega = \frac{\langle \mathbf{x}, \mathbf{y} \rangle}{\|\mathbf{x}\| \|\mathbf{y}\|} = -\frac{1}{3} \implies \omega \approx 1.91 \text{ rad} \approx 109.5^\circ, \quad (3.29)$$

and \mathbf{x} and \mathbf{y} are not orthogonal. Therefore, vectors that are orthogonal with respect to one inner product do not have to be orthogonal with respect to a different inner product.

3.5 Inner Products of Functions

Thus far, we looked at properties of inner products to compute lengths, angles and distances. We focused on inner products of finite-dimensional vectors.

In the following, we will look at an example of inner products of a different type of vectors: inner products of functions.

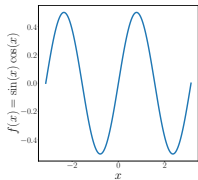
The inner products we discussed so far were defined for vectors with a finite number of entries. We can think of these vectors as discrete functions with a finite number of function values. The concept of an inner product can be generalized to vectors with an infinite number of entries (countably infinite) and also continuous-valued functions (uncountably infinite). Then, the sum over individual components of vectors, see (3.6) for example, turns into an integral.

An inner product of two functions $u : \mathbb{R} \rightarrow \mathbb{R}$ and $v : \mathbb{R} \rightarrow \mathbb{R}$ can be defined as the definite integral

$$\langle u, v \rangle := \int_a^b u(x)v(x)dx \quad (3.30)$$

for lower and upper limits $a, b < \infty$, respectively. As with our usual inner product, we can define norms and orthogonality by looking at the inner product. If (3.30) evaluates to 0, the functions u and v are orthogonal. To make the above inner product mathematically precise, we need to take care of measures, and the definition of integrals. Furthermore, unlike inner product on finite dimensional vectors, inner products on functions may diverge (have infinite value). Some careful definitions need to be observed, which requires a foray into real and functional analysis which we do not cover in this book.

Figure 3.7 $f(x) = \sin(x) \cos(x)$.



Example (Inner Product of Functions)

If we choose $u = \sin(x)$ and $v = \cos(x)$, the integrand $f(x) = u(x)v(x)$ of (3.30), is shown in Figure 3.7. We see that this function is odd, i.e., $f(-x) = -f(x)$. Therefore, the integral with limits $a = -\pi, b = \pi$ of this product evaluates to 0. Therefore, \sin and \cos are orthogonal functions.

Remark. It also holds that the collection of functions

$$\{1, \cos(x), \cos(2x), \cos(3x), \dots\} \quad (3.31)$$

is orthogonal if we integrate from $-\pi$ to π , i.e., any pair of functions are orthogonal to each other. \diamond

In Chapter 6, we will have a look at a second type of unconventional inner products: the inner product of random variables.

3.6 Orthogonal Projections

Projections are an important class of linear transformations (besides rotations and reflections). Projections play an important role in graphics, coding theory, statistics and machine learning. In machine learning, we often deal with data that is high-dimensional. High-dimensional data is often hard to analyze or visualize. However, high-dimensional data quite often

3.6 Orthogonal Projections

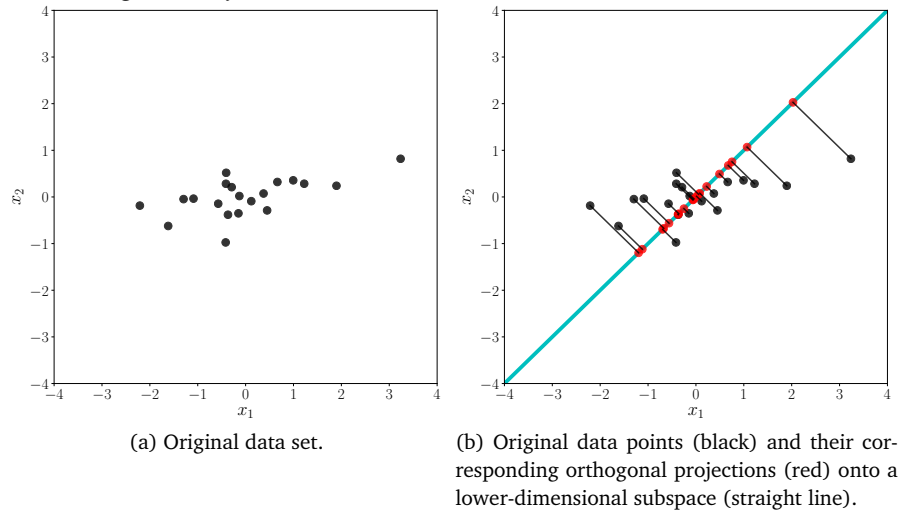


Figure 3.8
Orthogonal
projection of a
two-dimensional
data set onto a
one-dimensional
subspace.

possesses the property that only a few dimensions contain most information, and most other dimensions are not essential to describe key properties of the data. When we compress or visualize high-dimensional data we will lose information. To minimize this compression loss, we ideally find the most informative dimensions in the data. Then, we can project the original high-dimensional data onto a lower-dimensional feature space and work in this lower-dimensional space to learn more about the data set and extract patterns. For example, machine learning algorithms, such as Principal Component Analysis (PCA) by Pearson (1901); Hotelling (1933) and Deep Neural Networks (e.g., deep auto-encoders Deng et al. (2010)), heavily exploit the idea of dimensionality reduction. In the following, we will focus on orthogonal projections, which we will use in Chapter 10 for linear dimensionality reduction and in Chapter 12 for classification. Even linear regression, which we discuss in Chapter 9 can be interpreted using orthogonal projections. For a given lower-dimensional subspace, orthogonal projections of high-dimensional data retain as much information as possible and minimize the difference/error between the original data and the corresponding projection. An illustration of such an orthogonal projection is given in Figure 3.8.

Before we detail how to obtain these projections, let us define what a projection actually is.

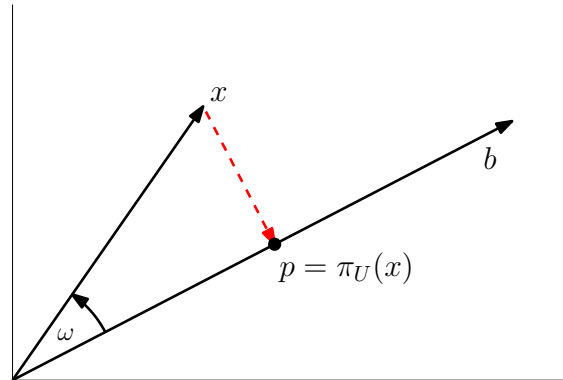
Definition 3.7 (Projection). Let V be a vector space and $W \subseteq V$ a subspace of V . A linear mapping $\pi : V \rightarrow W$ is called a *projection* if $\pi^2 = \pi \circ \pi = \pi$.

Remark (Projection matrix). Since linear mappings can be expressed by transformation matrices, the definition above applies equally to a special

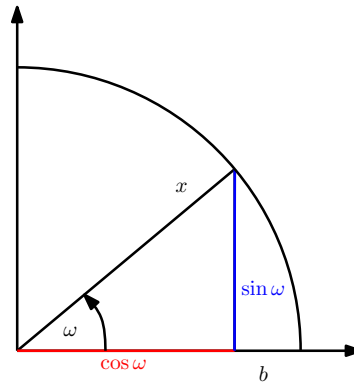
“Feature” is a
commonly used
word for “data
representation”.

Figure 3.9

Projection of $\mathbf{x} \in \mathbb{R}^2$ onto a subspace U with basis \mathbf{b} .

**Figure 3.10**

Projection of a two-dimensional vector \mathbf{x} onto a one-dimensional subspace with $\|\mathbf{x}\| = 1$.



kind of transformation matrices, the *projection matrices* \mathbf{P}_π , which exhibit the property that $\mathbf{P}_\pi^2 = \mathbf{P}_\pi$.

projection matrices

Since $\mathbf{P}_\pi^2 = \mathbf{P}_\pi$ it follows that all eigenvalues of \mathbf{P}_π are either 0 or 1. The corresponding eigenspaces are the kernel and image of the projection, respectively. More details about eigenvalues and eigenvectors are provided in Chapter 4. \diamond

A good illustration is given here:
<http://tinyurl.com/p5jn5ws>.

In the following, we will derive orthogonal projections of vectors in the inner product space $(\mathbb{R}^n, \langle \cdot, \cdot \rangle)$ onto subspaces. We will start with one-dimensional subspaces, which are also called *lines*. If not mentioned otherwise, we assume the dot product $\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^\top \mathbf{y}$ as the inner product.

lines

3.6.1 Projection onto 1-Dimensional Subspaces (Lines)

Assume we are given a line (1-dimensional subspace) through the origin with basis vector $\mathbf{b} \in \mathbb{R}^n$. The line is a one-dimensional subspace $U \subseteq \mathbb{R}^n$ spanned by \mathbf{b} . When we project $\mathbf{x} \in \mathbb{R}^n$ onto U , we want to find the point $\pi_U(\mathbf{x}) \in U$ that is closest to \mathbf{x} . Using geometric arguments, let us characterize some properties of the projection $\pi_U(\mathbf{x})$ (Fig. 3.9 serves as an illustration):

- The projection $\pi_U(\mathbf{x})$ is closest to \mathbf{x} , where “closest” implies that the distance $\|\mathbf{x} - \pi_U(\mathbf{x})\|$ is minimal. It follows that the segment $\pi_U(\mathbf{x}) - \mathbf{x}$ from $\pi_U(\mathbf{x})$ to \mathbf{x} is orthogonal to U and, therefore, the basis \mathbf{b} of U . The orthogonality condition yields $\langle \pi_U(\mathbf{x}) - \mathbf{x}, \mathbf{b} \rangle = 0$ since angles between vectors are defined by means of the inner product.
- The projection $\pi_U(\mathbf{x})$ of \mathbf{x} onto U must be an element of U and, therefore, a multiple of the basis vector \mathbf{b} that spans U . Hence, $\pi_U(\mathbf{x}) = \lambda \mathbf{b}$, for some $\lambda \in \mathbb{R}$.

λ is then the coordinate of $\pi_U(\mathbf{x})$ with respect to \mathbf{b} .

In the following three steps, we determine the coordinate λ , the projection $\pi_U(\mathbf{x}) \in U$ and the projection matrix \mathbf{P}_π that maps arbitrary $\mathbf{x} \in \mathbb{R}^n$ onto U .

1. Finding the coordinate λ . The orthogonality condition yields

$$\langle \mathbf{x} - \pi_U(\mathbf{x}), \mathbf{b} \rangle = 0 \quad (3.32)$$

$$\xLeftrightarrow{\pi_U(\mathbf{x}) = \lambda \mathbf{b}} \langle \mathbf{x} - \lambda \mathbf{b}, \mathbf{b} \rangle = 0. \quad (3.33)$$

We can now exploit the bilinearity of the inner product and arrive at

$$\langle \mathbf{x}, \mathbf{b} \rangle - \lambda \langle \mathbf{b}, \mathbf{b} \rangle = 0 \quad (3.34)$$

$$\Leftrightarrow \lambda = \frac{\langle \mathbf{x}, \mathbf{b} \rangle}{\langle \mathbf{b}, \mathbf{b} \rangle} = \frac{\langle \mathbf{x}, \mathbf{b} \rangle}{\|\mathbf{b}\|^2} \quad (3.35)$$

With a general inner product, we get $\lambda = \langle \mathbf{x}, \mathbf{b} \rangle$ if $\|\mathbf{b}\| = 1$.

If we choose $\langle \cdot, \cdot \rangle$ to be the dot product, we obtain

$$\lambda = \frac{\mathbf{b}^\top \mathbf{x}}{\mathbf{b}^\top \mathbf{b}} = \frac{\mathbf{b}^\top \mathbf{x}}{\|\mathbf{b}\|^2} \quad (3.36)$$

If $\|\mathbf{b}\| = 1$, then the coordinate λ of the projection is given by $\mathbf{b}^\top \mathbf{x}$.

2. Finding the projection point $\pi_U(\mathbf{x}) \in U$. Since $\pi_U(\mathbf{x}) = \lambda \mathbf{b}$ we immediately obtain with (3.36) that

$$\pi_U(\mathbf{x}) = \lambda \mathbf{b} = \frac{\langle \mathbf{x}, \mathbf{b} \rangle}{\|\mathbf{b}\|^2} \mathbf{b} = \frac{\mathbf{b}^\top \mathbf{x}}{\|\mathbf{b}\|^2} \mathbf{b}, \quad (3.37)$$

where the last equality holds for the dot product only. We can also compute the length of $\pi_U(\mathbf{x})$ by means of Definition 3.1 as

$$\|\mathbf{p}\| = \|\lambda \mathbf{b}\| = |\lambda| \|\mathbf{b}\|. \quad (3.38)$$

This means that our projection is of length $|\lambda|$ times the length of \mathbf{b} . This also adds the intuition that λ is the coordinate of $\pi_U(\mathbf{x})$ with respect to the basis vector \mathbf{b} that spans our one-dimensional subspace U .

If we use the dot product as an inner product we get

$$\|\pi_U(\mathbf{x})\| \stackrel{(3.37)}{=} \frac{|\mathbf{b}^\top \mathbf{x}|}{\|\mathbf{b}\|^2} \|\mathbf{b}\| \stackrel{(3.26)}{=} |\cos \omega| \|\mathbf{x}\| \|\mathbf{b}\| \frac{\|\mathbf{b}\|}{\|\mathbf{b}\|^2} = |\cos \omega| \|\mathbf{x}\|. \quad (3.39)$$

The horizontal axis is a one-dimensional subspace.

Here, ω is the angle between \mathbf{x} and \mathbf{b} . This equation should be familiar from trigonometry: If $\|\mathbf{x}\| = 1$ then \mathbf{x} lies on the unit circle. It follows that the projection onto the horizontal axis spanned by \mathbf{b} is exactly $\cos \omega$, and the length of the corresponding vector $\pi_U(\mathbf{x}) = |\cos \omega|$. An illustration is given in Figure 3.10.

3. Finding the projection matrix \mathbf{P}_π . We know that a projection is a linear mapping (see Definition 3.7). Therefore, there exists a projection matrix \mathbf{P}_π , such that $\pi_U(\mathbf{x}) = \mathbf{P}_\pi \mathbf{x}$. With the dot product as inner product and

$$\pi_U(\mathbf{x}) = \lambda \mathbf{b} = \mathbf{b} \lambda = \mathbf{b} \frac{\mathbf{b}^\top \mathbf{x}}{\|\mathbf{b}\|^2} = \frac{\mathbf{b} \mathbf{b}^\top}{\|\mathbf{b}\|^2} \mathbf{x} \quad (3.40)$$

we immediately see that

$$\mathbf{P}_\pi = \frac{\mathbf{b} \mathbf{b}^\top}{\|\mathbf{b}\|^2}. \quad (3.41)$$

Projection matrices are always symmetric.

Note that $\mathbf{b} \mathbf{b}^\top$ is a symmetric matrix (with rank 1) and $\|\mathbf{b}\|^2 = \langle \mathbf{b}, \mathbf{b} \rangle$ is a scalar.

The projection matrix \mathbf{P}_π projects any vector $\mathbf{x} \in \mathbb{R}^n$ onto the line through the origin with direction \mathbf{b} (equivalently, the subspace U spanned by \mathbf{b}).

Remark. The projection $\pi_U(\mathbf{x}) \in \mathbb{R}^n$ is still an n -dimensional vector and not a scalar. However, we no longer require n coordinates to represent the projection, but only a single one if we want to express it with respect to the basis vector \mathbf{b} that spans the subspace U : λ . \diamond

Example (Projection onto a Line)

Find the projection matrix \mathbf{P}_π onto the line through the origin spanned by $\mathbf{b} = \begin{bmatrix} 1 & 2 & 2 \end{bmatrix}^\top$. \mathbf{b} is a direction and a basis of the one-dimensional subspace (line through origin).

With (3.41), we obtain

$$\mathbf{P}_\pi = \frac{\mathbf{b} \mathbf{b}^\top}{\mathbf{b}^\top \mathbf{b}} = \frac{1}{9} \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} \begin{bmatrix} 1 & 2 & 2 \end{bmatrix} = \frac{1}{9} \begin{bmatrix} 1 & 2 & 2 \\ 2 & 4 & 4 \\ 2 & 4 & 4 \end{bmatrix}. \quad (3.42)$$

Let us now choose a particular \mathbf{x} and see whether it lies in the subspace spanned by \mathbf{b} . For $\mathbf{x} = \begin{bmatrix} 1 & 1 & 1 \end{bmatrix}^\top$, the projected point is

$$\pi_U(\mathbf{x}) = \mathbf{P}_\pi \mathbf{x} = \frac{1}{9} \begin{bmatrix} 1 & 2 & 2 \\ 2 & 4 & 4 \\ 2 & 4 & 4 \end{bmatrix} \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = \frac{1}{9} \begin{bmatrix} 5 \\ 10 \\ 10 \end{bmatrix} \in \text{span} \left[\begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} \right]. \quad (3.43)$$

Note that the application of \mathbf{P}_π to $\pi_U(\mathbf{x})$ does not change anything, i.e., $\mathbf{P}_\pi \pi_U(\mathbf{x}) = \pi_U(\mathbf{x})$. This is expected because according to Definition 3.7

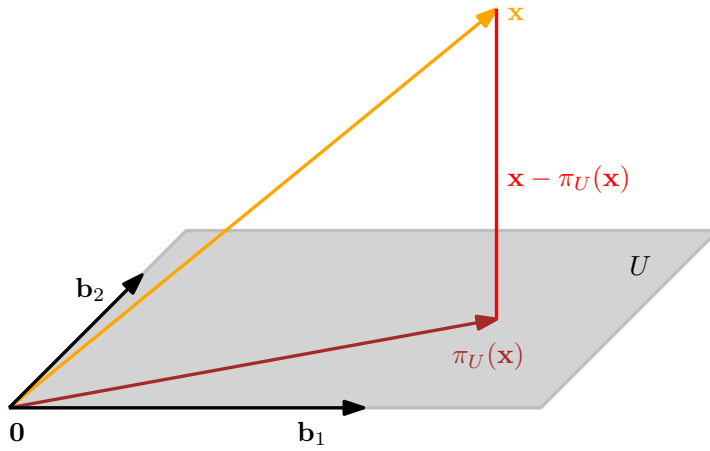


Figure 3.11
Projection onto a two-dimensional subspace U with basis $\mathbf{b}_1, \mathbf{b}_2$. The projection $\pi_U(\mathbf{x})$ of $\mathbf{x} \in \mathbb{R}^3$ onto U can be expressed as a linear combination of $\mathbf{b}_1, \mathbf{b}_2$ and the displacement vector $\mathbf{x} - \pi_U(\mathbf{x})$ is orthogonal to both \mathbf{b}_1 and \mathbf{b}_2 .

we know that a projection matrix \mathbf{P}_π satisfies $\mathbf{P}_\pi^2 \mathbf{x} = \mathbf{P}_\pi \mathbf{x}$. Therefore, $\pi_U(\mathbf{x})$ is also an eigenvector of \mathbf{P}_π , and the corresponding eigenvalue is 1.

3.6.2 Projection onto General Subspaces

In the following, we look at orthogonal projections of vectors $\mathbf{x} \in \mathbb{R}^n$ onto higher-dimensional subspaces $U \subseteq \mathbb{R}^n$ with $\dim(U) = m \geq 1$. An illustration is given in Figure 3.11.

Assume that $(\mathbf{b}_1, \dots, \mathbf{b}_m)$ is an ordered basis of U . Any projection $\pi_U(\mathbf{x})$ onto U is necessarily an element of U . Therefore, they can be represented as linear combinations of the basis vectors $\mathbf{b}_1, \dots, \mathbf{b}_m$ of U , such that $\pi_U(\mathbf{x}) = \sum_{i=1}^m \lambda_i \mathbf{b}_i$.

As in the 1D case, we follow a three-step procedure to find the projection $\pi_U(\mathbf{x})$ and the projection matrix \mathbf{P}_π :

1. Find the coordinates $\lambda_1, \dots, \lambda_m$ of the projection (with respect to the basis of U), such that the linear combination

$$\pi_U(\mathbf{x}) = \sum_{i=1}^m \lambda_i \mathbf{b}_i = \mathbf{B}\boldsymbol{\lambda}, \quad (3.44)$$

$$\mathbf{B} = [\mathbf{b}_1, \dots, \mathbf{b}_m] \in \mathbb{R}^{n \times m}, \quad \boldsymbol{\lambda} = [\lambda_1, \dots, \lambda_m]^\top \in \mathbb{R}^m, \quad (3.45)$$

is closest to $\mathbf{x} \in \mathbb{R}^n$. As in the 1D case, “closest” means “minimum distance”, which implies that the vector connecting $\pi_U(\mathbf{x}) \in U$ and $\mathbf{x} \in \mathbb{R}^n$ must be orthogonal to all basis vectors of U . Therefore, we obtain m simultaneous conditions (assuming the dot product as the inner product)

$$\langle \mathbf{b}_1, \mathbf{x} - \pi_U(\mathbf{x}) \rangle = \mathbf{b}_1^\top (\mathbf{x} - \pi_U(\mathbf{x})) = 0 \quad (3.46)$$

If U is given by a set of spanning vectors, which are not a basis, make sure you determine a basis $\mathbf{b}_1, \dots, \mathbf{b}_m$ before proceeding.

The basis vectors form the columns of $\mathbf{B} \in \mathbb{R}^{n \times m}$, where $\mathbf{B} = [\mathbf{b}_1, \dots, \mathbf{b}_m]$.

$$\vdots \quad (3.47)$$

$$\langle \mathbf{b}_m, \mathbf{x} - \pi_U(\mathbf{x}) \rangle = \mathbf{b}_m^\top (\mathbf{x} - \pi_U(\mathbf{x})) = 0 \quad (3.48)$$

which, with $\pi_U(\mathbf{x}) = \mathbf{B}\boldsymbol{\lambda}$, can be written as

$$\mathbf{b}_1^\top (\mathbf{x} - \mathbf{B}\boldsymbol{\lambda}) = 0 \quad (3.49)$$

$$\vdots \quad (3.50)$$

$$\mathbf{b}_m^\top (\mathbf{x} - \mathbf{B}\boldsymbol{\lambda}) = 0 \quad (3.51)$$

such that we obtain a homogeneous linear equation system

$$\begin{bmatrix} \mathbf{b}_1^\top \\ \vdots \\ \mathbf{b}_m^\top \end{bmatrix} \begin{bmatrix} \mathbf{x} - \mathbf{B}\boldsymbol{\lambda} \end{bmatrix} = \mathbf{0} \iff \mathbf{B}^\top (\mathbf{x} - \mathbf{B}\boldsymbol{\lambda}) = \mathbf{0} \quad (3.52)$$

$$\iff \mathbf{B}^\top \mathbf{B}\boldsymbol{\lambda} = \mathbf{B}^\top \mathbf{x}. \quad (3.53)$$

normal equation

The last expression is called *normal equation*. Since $\mathbf{b}_1, \dots, \mathbf{b}_m$ are a basis of U and, therefore, linearly independent, $\mathbf{B}^\top \mathbf{B} \in \mathbb{R}^{m \times m}$ is regular and can be inverted. This allows us to solve for the coefficients/coordinates

$$\boldsymbol{\lambda} = (\mathbf{B}^\top \mathbf{B})^{-1} \mathbf{B}^\top \mathbf{x}. \quad (3.54)$$

pseudo-inverse

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The matrix $(\mathbf{B}^\top \mathbf{B})^{-1} \mathbf{B}^\top$ is also called the *pseudo-inverse* of \mathbf{B} , which can be computed for non-square matrices \mathbf{B} . It only requires that $\mathbf{B}^\top \mathbf{B}$ is positive definite, which is the case if \mathbf{B} is full rank.¹

2. Find the projection $\pi_U(\mathbf{x}) \in U$. We already established that $\pi_U(\mathbf{x}) = \mathbf{B}\boldsymbol{\lambda}$. Therefore, with (3.54)

$$\pi_U(\mathbf{x}) = \mathbf{p} = \mathbf{B}(\mathbf{B}^\top \mathbf{B})^{-1} \mathbf{B}^\top \mathbf{x}. \quad (3.55)$$

3. Find the projection matrix \mathbf{P}_π . From (3.55) we can immediately see that the projection matrix that solves $\mathbf{P}_\pi \mathbf{x} = \pi_U(\mathbf{x})$ must be

$$\mathbf{P}_\pi = \mathbf{B}(\mathbf{B}^\top \mathbf{B})^{-1} \mathbf{B}^\top. \quad (3.56)$$

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Remark. Comparing the solutions for projecting onto a one-dimensional subspace and the general case, we see that the general case includes the 1D case as a special case: If $\dim(U) = 1$ then $\mathbf{B}^\top \mathbf{B} \in \mathbb{R}$ is a scalar and we can rewrite the projection matrix in (3.56) (either give equation number or repeat the equation but not both, i would just give the eq. number) $\mathbf{P}_\pi = \mathbf{B}(\mathbf{B}^\top \mathbf{B})^{-1} \mathbf{B}^\top$ as $\mathbf{P}_\pi = \frac{\mathbf{B}\mathbf{B}^\top}{\mathbf{B}^\top \mathbf{B}}$, which is exactly the projection matrix in (3.41). \diamond

¹In practical applications (e.g., linear regression), we often add a “jitter term” $\epsilon \mathbf{I}$ to $\mathbf{B}^\top \mathbf{B}$ to guarantee increase numerical stability and positive definiteness. This “ridge” can be rigorously derived using Bayesian inference. See Chapter 9 for details.

Example (Projection onto a Two-dimensional Subspace)

For a subspace $U = \text{span}\left[\begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 2 \end{bmatrix}\right] \subseteq \mathbb{R}^3$ and $\mathbf{x} = \begin{bmatrix} 6 \\ 0 \\ 0 \end{bmatrix} \in \mathbb{R}^3$ find the coordinates $\boldsymbol{\lambda}$ of \mathbf{x} in terms of the subspace U , the projection point $\pi_U(\mathbf{x})$ and the projection matrix \mathbf{P}_π .

First, we see that the generating set of U is a basis (linear independence) and write the basis vectors of U into a matrix $\mathbf{B} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \end{bmatrix}$.

Second, we compute the matrix $\mathbf{B}^\top \mathbf{B}$ and the vector $\mathbf{B}^\top \mathbf{x}$ as

$$\mathbf{B}^\top \mathbf{B} = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \end{bmatrix} = \begin{bmatrix} 3 & 3 \\ 3 & 5 \end{bmatrix}, \quad \mathbf{B}^\top \mathbf{x} = \begin{bmatrix} 1 & 1 & 1 \\ 0 & 1 & 2 \end{bmatrix} \begin{bmatrix} 6 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 6 \\ 0 \end{bmatrix}. \quad (3.57)$$

Third, we solve the normal equation $\mathbf{B}^\top \mathbf{B} \boldsymbol{\lambda} = \mathbf{B}^\top \mathbf{x}$ to find $\boldsymbol{\lambda}$:

$$\begin{bmatrix} 3 & 3 \\ 3 & 5 \end{bmatrix} \begin{bmatrix} \lambda_1 \\ \lambda_2 \end{bmatrix} = \begin{bmatrix} 6 \\ 0 \end{bmatrix} \iff \boldsymbol{\lambda} = \begin{bmatrix} 5 \\ -3 \end{bmatrix}. \quad (3.58)$$

Fourth, the projection $\pi_U(\mathbf{x})$ of \mathbf{x} onto U , i.e., into the column space of \mathbf{B} , can be directly computed via

$$\pi_U(\mathbf{x}) = \mathbf{B} \boldsymbol{\lambda} = \begin{bmatrix} 5 \\ 2 \\ -1 \end{bmatrix}. \quad (3.59)$$

The corresponding *projection error* is the norm of the distance between the original vector and its projection onto U , i.e.,

$$\|\mathbf{x} - \pi_U(\mathbf{x})\| = \left\| \begin{bmatrix} 1 & -2 & 1 \end{bmatrix}^\top \right\| = \sqrt{6}. \quad (3.60)$$

Fifth, the projection matrix (for any $\mathbf{x} \in \mathbb{R}^3$) is given by

$$\mathbf{P}_\pi = \mathbf{B}(\mathbf{B}^\top \mathbf{B})^{-1} \mathbf{B}^\top = \frac{1}{6} \begin{bmatrix} 5 & 2 & -1 \\ 2 & 2 & 2 \\ -1 & 2 & 5 \end{bmatrix}. \quad (3.61)$$

To verify the results, we can (a) check whether the displacement vector $\pi_U(\mathbf{x}) - \mathbf{x}$ is orthogonal to all basis vectors of U , (b) verify that $\mathbf{P}_\pi = \mathbf{P}_\pi^2$ (see Definition 3.7).

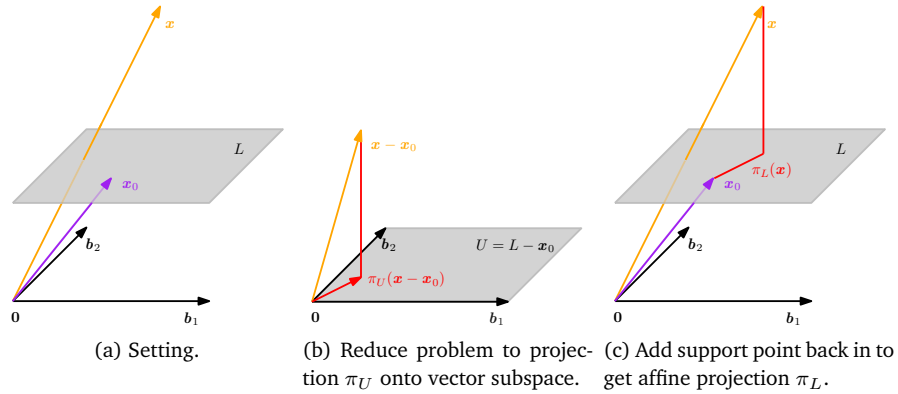
projection error

The projection error is also called the *reconstruction error*.

Remark. The projections $\pi_U(\mathbf{x})$ are still vectors in \mathbb{R}^n although they lie in an m -dimensional subspace $U \subseteq \mathbb{R}^n$. However, to represent a projected

Figure 3.12

Projection onto an affine space. (a) The original setting; (b) The setting is shifted by $-x_0$, so that $x - x_0$ can be projected onto the direction space U ; (c) The projection is translated back to $x_0 + \pi_U(x - x_0)$, which gives the final orthogonal projection $\pi_L(x)$.



vector we only need the m coordinates $\lambda_1, \dots, \lambda_m$ with respect to the basis vectors b_1, \dots, b_m of U . \diamond

Remark. In vector spaces with general inner products, we have to pay attention when computing angles and distances, which are defined by means of the inner product. \diamond

We can find approximate solutions to unsolvable linear equation systems using projections.

Projections allow us to look at situations where we have a linear system $Ax = b$ without a solution. Recall that this means that b does not lie in the span of A , i.e., the vector b does not lie in the subspace spanned by the columns of A . Given that the linear equation cannot be solved exactly, we can find an *approximate solution*. The idea is to find the vector in the subspace spanned by the columns of A that is closest to b , i.e., we compute the orthogonal projection of b onto the subspace spanned by the columns of A . This problem arises often in practice, and the solution is called the *least squares solution* (assuming the dot product as the inner product) of an overdetermined system. This is discussed further in Chapter 9.

least squares solution

3.6.3 Projection onto Affine Subspaces

Thus far, we discussed how to project a vector onto a lower-dimensional subspace U . In the following, we provide a solution to projecting a vector onto an affine subspace.

Consider the setting in Figure 3.12(a). We are given an affine space $L = x_0 + U$ where b_1, b_2 are basis vectors of U . To determine the orthogonal projection $\pi_L(x)$ of x onto L , we transform the problem into a problem that we know how to solve: the projection onto a vector subspace. In order to get there, we subtract the support point x_0 from x and from L , so that $L - x_0 = U$ is exactly the vector subspace U . We can now use the orthogonal projections onto a subspace we discussed in Section 3.6.2 and obtain the projection $\pi_U(x - x_0)$, which is illustrated in Figure 3.12(b). This projection can now be translated back into L by adding x_0 , such that

we obtain the orthogonal projection onto an affine space L as

$$\pi_L(\mathbf{x}) = \mathbf{x}_0 + \pi_U(\mathbf{x} - \mathbf{x}_0), \quad (3.62)$$

where $\pi_U(\cdot)$ is the orthogonal projection onto the subspace U , i.e., the direction space of L , see Figure 3.12(c).

From Figure 3.12 it is also evident that the distance of \mathbf{x} from the affine space L is identical to the distance of $\mathbf{x} - \mathbf{x}_0$ from U , i.e.,

$$d(\mathbf{x}, L) = \|\mathbf{x} - \pi_L(\mathbf{x})\| = \|\mathbf{x} - (\mathbf{x}_0 + \pi_U(\mathbf{x} - \mathbf{x}_0))\| \quad (3.63)$$

$$= d(\mathbf{x} - \mathbf{x}_0, \pi_U(\mathbf{x} - \mathbf{x}_0)). \quad (3.64)$$

3.7 Orthonormal Basis

In Section 2.6.1, we characterized properties of basis vectors and found that in an n -dimensional vector space, we need n basis vectors, i.e., n vectors that are linearly independent. In Sections 3.3 and 3.4, we used inner products to compute the length of vectors and the angle between vectors. In the following, we will discuss the special case where the basis vectors are orthogonal to each other and where the length of each basis vector is 1. We will call this basis then an orthonormal basis.

Let us introduce this more formally.

Definition 3.8 (Orthonormal basis). Consider an n -dimensional vector space V and a basis $\{\mathbf{b}_1, \dots, \mathbf{b}_n\}$ of V . If

$$\langle \mathbf{b}_i, \mathbf{b}_j \rangle = 0 \quad \text{for } i \neq j \quad (3.65)$$

$$\langle \mathbf{b}_i, \mathbf{b}_i \rangle = 1 \quad (3.66)$$

for all $i, j = 1, \dots, n$ then the basis is called an *orthonormal basis* (ONB). If only (3.65) is satisfied and then the basis is called an *orthogonal basis*.

orthonormal basis
ONB
orthogonal basis

Note that (3.66) implies that every basis vector has length/norm 1. The Gram-Schmidt process (Strang, 2003) is a constructive way to iteratively build an orthonormal basis $\{\mathbf{b}_1, \dots, \mathbf{b}_n\}$ given a set $\{\tilde{\mathbf{b}}_1, \dots, \tilde{\mathbf{b}}_n\}$ of non-orthogonal and unnormalized basis vectors.

Example (Orthonormal basis)

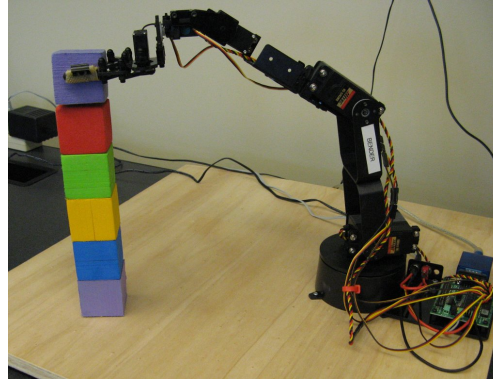
The canonical/standard basis for a Euclidean vector space \mathbb{R}^n is an orthonormal basis, where the inner product is the dot product of vectors.

In \mathbb{R}^2 , the vectors

$$\mathbf{b}_1 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \quad \mathbf{b}_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \end{bmatrix} \quad (3.67)$$

form an orthonormal basis since $\mathbf{b}_1^\top \mathbf{b}_2 = 0$ and $\|\mathbf{b}_1\| = 1 = \|\mathbf{b}_2\|$.

Figure 3.13 The robotic arm needs to rotate its joints in order to pick up objects or to place them correctly. Figure taken from (Deisenroth et al., 2015).



In Section 3.6, we derived projections of vectors x onto a subspace U with basis vectors $\{b_1, \dots, b_k\}$. If this basis is an ONB, i.e., (3.65)–(3.66) are satisfied, the projection equation (3.55) simplifies greatly to

$$\pi_U(x) = BB^T x \quad (3.68)$$

since $B^T B = I$. This means that we no longer have to compute the tedious inverse from (3.55), which saves us much computation time.

We will exploit the concept of an orthonormal basis in Chapter 12 and Chapter 10 when we discuss Support Vector Machines and Principal Component Analysis.

3.8 Rotations

An important category of linear mappings are rotations. A rotation is acting to rotate an object (counterclockwise) by an angle θ about the origin. Important application areas of rotations include computer graphics and robotics. For example, in robotics, it is often important to know how to rotate the joints of a robotic arm in order to pick up or place an object, see Figure 3.13.

3.8.1 Rotations in the Plane

Consider the standard basis in \mathbb{R}^2 $\left\{ e_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}, e_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix} \right\}$, which defines the standard coordinate system in \mathbb{R}^2 . Assume we want to rotate this coordinate system by an angle θ as illustrated in Figure 3.14. Note that the rotated vectors are still linearly independent and, therefore, are a basis of \mathbb{R}^2 . This means that the rotation performs a basis change.

Since rotations Φ are linear mappings, we can express them by a *rotation matrix* $R(\theta)$. Trigonometry allows us to determine the coordinates of the

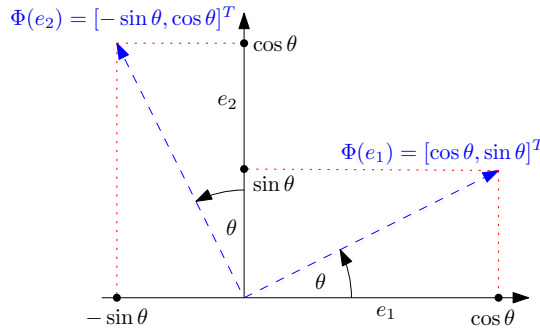


Figure 3.14
Rotation of the
standard basis in \mathbb{R}^2
by an angle θ .

rotated axes with respect to the standard basis in \mathbb{R}^2 . We obtain

$$\Phi(e_1) = \begin{bmatrix} \cos \theta \\ \sin \theta \end{bmatrix}, \quad \Phi(e_2) = \begin{bmatrix} -\sin \theta \\ \cos \theta \end{bmatrix}. \quad (3.69)$$

Therefore, the rotation matrix that performs the basis change into the rotated coordinates $\mathbf{R}(\theta)$ is given as

$$\mathbf{R}(\theta) = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \quad (3.70)$$

Generally, in \mathbb{R}^2 rotations of any vector $\mathbf{x} \in \mathbb{R}^2$ by an angle θ are given by

$$\mathbf{x}' = \Phi(\mathbf{x}) = \mathbf{R}(\theta)\mathbf{x} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} x_1 \cos \theta - x_2 \sin \theta \\ x_1 \sin \theta + x_2 \cos \theta \end{bmatrix}. \quad (3.71)$$

3.8.2 Rotations in Three Dimensions

In three dimensions, we have to define what “counterclockwise” means: We will go by the convention that a “counterclockwise” (planar) rotation about an axis refers to a rotation about an axis when we look at the axis “from the end toward the origin”. In \mathbb{R}^3 there are three (planar) rotations about three standard basis vectors (see Figure 3.15):

- Counterclockwise rotation about the e_1 -axis

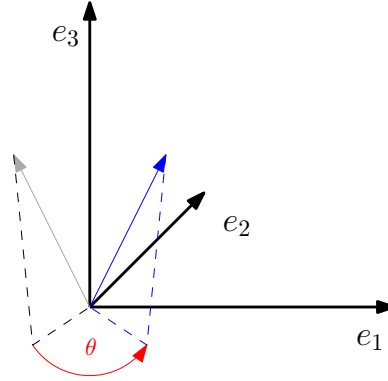
$$\mathbf{R}_1(\theta) = [\Phi(e_1) \quad \Phi(e_2) \quad \Phi(e_3)] = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \theta & -\sin \theta \\ 0 & \sin \theta & \cos \theta \end{bmatrix} \quad (3.72)$$

Here, the e_1 coordinate is fixed, and the counterclockwise rotation is performed in the e_2e_3 plane.

- Counterclockwise rotation about the e_2 -axis

$$\mathbf{R}_2(\theta) = \begin{bmatrix} \cos \theta & 0 & \sin \theta \\ 0 & 1 & 0 \\ -\sin \theta & 0 & \cos \theta \end{bmatrix} \quad (3.73)$$

Figure 3.15
Rotation of a vector (gray) in \mathbb{R}^3 by an angle θ about the e_3 -axis. The rotated vector is shown in blue.



1754 If we rotate the e_1e_3 plane about the e_2 axis, we need to look at the e_2
1755 axis from its “tip” toward the origin.

- Counterclockwise rotation about the e_3 -axis

$$\mathbf{R}_3(\theta) = \begin{bmatrix} \cos \theta & -\sin \theta & 0 \\ \sin \theta & \cos \theta & 0 \\ 0 & 0 & 1 \end{bmatrix}. \quad (3.74)$$

1756 Figure 3.15 illustrates this.

3.8.3 Rotations in n Dimensions

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1758 The generalization of rotations from 2D and 3D to n -dimensional Euclidean vector spaces can be intuitively described as keeping $n - 2$ di-
1759 mensions fix and restrict the rotation to a two-dimensional plane in the
1760 n -dimensional space.
1761

Definition 3.9 (Givens Rotation). Let V be an n -dimensional Euclidean vector space and $\Phi : V \rightarrow V$ an automorphism with transformation matrix

$$\mathbf{R}_{ij}(\theta) := \begin{bmatrix} \mathbf{I}_{i-1} & \mathbf{0} & \cdots & \cdots & \mathbf{0} \\ \mathbf{0} & \cos \theta & \mathbf{0} & -\sin \theta & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{I}_{j-i-1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \sin \theta & \mathbf{0} & \cos \theta & \mathbf{0} \\ \mathbf{0} & \cdots & \cdots & \mathbf{0} & \mathbf{I}_{n-j} \end{bmatrix} \in \mathbb{R}^{n \times n}, \quad \theta \in \mathbb{R}, \quad (3.75)$$

Givens rotation

for $1 \leq i < j \leq n$. Then $\mathbf{R}_{ij}(\theta)$ is called a *Givens rotation*. Essentially, $\mathbf{R}_{ij}(\theta)$ is the identity matrix \mathbf{I}_n with

$$r_{ii} = \cos \theta, \quad r_{ij} = -\sin \theta, \quad r_{ji} = \sin \theta, \quad r_{jj} = \cos \theta. \quad (3.76)$$

1762 In two dimensions (i.e., $n = 2$), we obtain (3.70) as a special case.

3.8.4 Properties of Rotations

Rotations exhibit some useful properties:

- The composition of rotations can be expressed as a single rotation where the angles are summed up:

$$\mathbf{R}(\phi)\mathbf{R}(\theta) = \mathbf{R}(\phi + \theta) \quad (3.77)$$

- Rotations preserve lengths, i.e., $\|\mathbf{x}\| = \|\mathbf{R}(\phi)\mathbf{x}\|$. The original vector and the rotated vector have the same length. This also implies that $\det(\mathbf{R}(\phi)) = 1$
- Rotations preserve distances, i.e., $\|\mathbf{x} - \mathbf{y}\| = \|\mathbf{R}_\theta(\mathbf{x}) - \mathbf{R}_\theta(\mathbf{y})\|$. In other words, rotations leave the distance between any two points unchanged after the transformation
- Rotations in three (or more) dimensions are generally not commutative. Therefore, the order in which rotations are applied is important, even if they rotate about the same point. Only in two dimensions vector rotations are commutative, such that $\mathbf{R}(\phi)\mathbf{R}(\theta) = \mathbf{R}(\theta)\mathbf{R}(\phi)$ for all $\phi, \theta \in [0, 2\pi)$, and form an Abelian group (with multiplication) if they rotate about the same point (e.g., the origin).
- Rotations have no real eigenvalues, except we rotate about $n\pi$ where $n \in \mathbb{Z}$.

Rotations preserve lengths and distances. Rotations are not commutative.

3.9 Further Reading

In this chapter, we gave a brief overview of some of the important concepts of analytic geometry, which we will use in later chapters of the book. For a broader and more in-depth overview of some the concepts we presented we refer to the excellent book by Boyd and Vandenberghe (2018), for example.

Inner products allow us to determine specific bases of vector (sub)spaces, where each vector is orthogonal to all others (orthogonal bases) using the Gram-Schmidt method. These bases are important in optimization and numerical algorithms for solving linear equation systems. For instance, Krylov subspace methods, such as Conjugate Gradients or GMRES, minimize residual errors that are orthogonal to each other (Stoer and Burlirsch, 2002).

In machine learning, inner products are important in the context of kernel methods (Schölkopf and Smola, 2002). Kernel methods exploit the fact that many linear algorithms can be expressed purely by inner product computations. Then, the “kernel trick” allows us to compute these inner products implicitly in a (potentially infinite-dimensional) feature space, without even knowing this feature space explicitly. This allowed the “non-linearization” of many algorithms used in machine learning, such as kernel-PCA (Schölkopf et al., 1997) for dimensionality reduction. Gaussian processes (Rasmussen and Williams, 2006) also fall into the category

of kernel methods and are the current state-of-the-art in probabilistic regression (fitting curves to data points). The idea of kernels is explored further in Chapter 12.

Projections are often used in computer graphics, e.g., to generate shadows. In optimization, orthogonal projections are often used to (iteratively) minimize residual errors. This also has applications in machine learning, e.g., in linear regression where we want to find a (linear) function that minimizes the residual errors, i.e., the lengths of the orthogonal projections of the data onto the linear function (Bishop, 2006). We will investigate this further in Chapter 9. PCA (Hotelling, 1933; Pearson, 1901) also uses projections to reduce the dimensionality of high-dimensional data. We will discuss this in more detail in Chapter 10.

Exercises

3.1 Show that $\langle \cdot, \cdot \rangle$ defined for all $\mathbf{x} = (x_1, x_2)$ and $\mathbf{y} = (y_1, y_2)$ in \mathbb{R}^2 by:

$$\langle \mathbf{x}, \mathbf{y} \rangle := x_1 y_1 - (x_1 y_2 + x_2 y_1) + 2(x_2 y_2)$$

is an inner product.

3.2 Consider \mathbb{R}^2 with $\langle \cdot, \cdot \rangle$ defined for all \mathbf{x} and \mathbf{y} in \mathbb{R}^2 as:

$$\langle \mathbf{x}, \mathbf{y} \rangle := \mathbf{x}^\top \underbrace{\begin{bmatrix} 2 & 0 \\ 1 & 2 \end{bmatrix}}_{=: \mathbf{A}} \mathbf{y}$$

Is $\langle \cdot, \cdot \rangle$ an inner product?

3.3 Consider the Euclidean vector space \mathbb{R}^5 with the dot product. A subspace $U \subseteq \mathbb{R}^5$ and $\mathbf{x} \in \mathbb{R}^5$ are given by

$$U = \text{span} \left[\begin{bmatrix} 0 \\ -1 \\ 2 \\ 0 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ -3 \\ 1 \\ -1 \\ 2 \end{bmatrix}, \begin{bmatrix} -3 \\ 4 \\ 1 \\ 2 \\ 1 \end{bmatrix}, \begin{bmatrix} -1 \\ -3 \\ 5 \\ 0 \\ 7 \end{bmatrix} \right], \quad \mathbf{x} = \begin{bmatrix} -1 \\ -9 \\ -1 \\ 4 \\ 1 \end{bmatrix}$$

1. Determine the orthogonal projection $\pi_U(\mathbf{x})$ of \mathbf{x} onto U
2. Determine the distance $d(\mathbf{x}, U)$

3.4 Consider \mathbb{R}^3 with the inner product

$$\langle \mathbf{x}, \mathbf{y} \rangle := \mathbf{x}^\top \begin{bmatrix} 2 & 1 & 0 \\ 1 & 2 & -1 \\ 0 & -1 & 2 \end{bmatrix} \mathbf{y}.$$

Furthermore, we define $\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3$ as the standard/canonical basis in \mathbb{R}^3 .

1. Determine the orthogonal projection $\pi_U(\mathbf{e}_2)$ of \mathbf{e}_2 onto

$$U = \text{span}[\mathbf{e}_1, \mathbf{e}_3].$$

Hint: Orthogonality is defined through the inner product.

2. Compute the distance $d(\mathbf{e}_2, U)$.

- 1821 3. Draw the scenario: standard basis vectors and $\pi_U(e_2)$
- 1822 3.5 Prove the Cauchy-Schwarz inequality $|\langle x, y \rangle| \leq \|x\| \|y\|$ for $x, y \in V$, where
- 1823 V is a vector space.