# Points and Vectors in $\mathbb{R}^n$

Alex Nita

### 1 Points and Vectors

#### 1.1 Definitions

Т

**Definition 1.1** We denote *n*-dimensional Euclidean space by

$$\mathbb{R}^{n} = \underbrace{\mathbb{R}^{n} \times \cdots \times \mathbb{R}}_{= \{(x_{1}, \dots, x_{n}) \mid x_{i} \text{ is a real number}\}}^{n \text{ times}}$$
(1.1)

We will typically use capital letters P for the elements of  $\mathbb{R}^n$ , the *n*-tuples  $(x_1, \ldots, x_n)$ , when thought of as **points**, in the sense of positional location,

$$P = (x_1, \dots, x_n) \tag{1.2}$$

We may also think of the elements of  $\mathbb{R}^n$  as **vectors**, however, for example when working with things like velocities/forces/etc. ('vector quantities', typically residing in phase space rather than configuration space, in physics lingo). There is a certain notation which is found in both physics and math books, that emphasises the *vector* part of the elements of  $\mathbb{R}^n$ , and it is the *boldface* or arrow, and *angle-bracket* notations for the *n*-tuples:

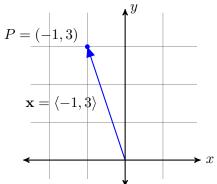
$$\mathbf{x}$$
 or  $\vec{x} = \langle x_1, \dots, x_n \rangle$  (1.3)

Add to this another notation for the *n*-tuples, needed for our own *linear-algebraic* purposes in this course: the *column vector* notation,

$$\mathbf{x} = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} \tag{1.4}$$

**Example 1.2** Our two main examples are the Euclidean plane  $\mathbb{R}^2$  and Euclidean three-dimensional space  $\mathbb{R}^3$ . We usually denote  $x_1$  by x,  $x_2$  by y, and  $x_3$  by z, so that P = (x, y) or (x, y, z), as the case may be.

We visualize points and vectors differently. For example, in  $\mathbb{R}^2$  the point P = (-1, 3) is pictured as a dot, and the vector  $\mathbf{x} = \langle -1, 3 \rangle$  is pictured as an arrow from the origin to P:



#### **1.2** Algebraic Properties of Vectors

The essential difference between points and vectors, mathematically, is that points don't possess any algebraic properties, whereas vectors do. The key algebraic properties of vectors are *addition*, *scalar multiplication*, and the *dot* and *cross products*:

- We can **add** two vectors.
- We can scale any vector (multiply it by a real number).
- Rules (1) and (2) are subject to certain rules (associativity, commutativity and distributivity rules). It's not so much that the rules make vectors 'nice' to work with, in the sense of a happy coincidence. The rules define the 'niceness' into the structure. The rules determine how all this works, and in the process give vectors a certain symbolic elegance with which to decorate their geometric import.
- We can **'multiply**' two vectors in various different ways. The most well-known and useful product is the **dot product** or **scalar product** of two vectors, which results in a real number. This is a product we'll study in greater depth in this course.
- The cross product of two vectors results, not in a real number, but in another vector. This product, so promising at first, runs into the difficulty of not generalizing well to higher dimensions, working only in  $\mathbb{R}^2$  and  $\mathbb{R}^3$ . It took some work, but Grassmann figured out how to get around this, by switching to the *wedge product* (see next bullet point).
- There are yet other products, such as the **tensor product**, the **wedge product** and the **Clifford product**, to name a few. They are studied in **geometric algebra** and **multilinear algebra**. If we have time towards the end of the semester we'll talk about some of these, too.

We'll begin with the definition of addition.

#### 1.2.1 Vector Addition

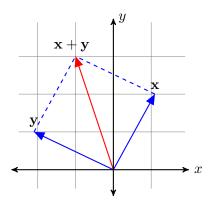
**Definition 1.3** We define addition of vectors in  $\mathbb{R}^n$  componentwise,

$$\mathbf{x} + \mathbf{y} = \langle x_1, x_2, \dots, x_n \rangle + \langle y_1, y_2, \dots, y_n \rangle$$
  
=  $\langle (x_1 + y_1), (x_2 + y_2), \dots, (x_n + y_n) \rangle$  (1.5)

This is more easily seen in terms of columns:

$$\mathbf{x} + \mathbf{y} = \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} + \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} x_1 + y_1 \\ x_2 + y_2 \\ \vdots \\ x_n + y_n \end{pmatrix}$$
(1.6)

**Example 1.4** Let us see what this means in  $\mathbb{R}^2$ . Take, say,  $\mathbf{x} = \langle 1, 2 \rangle$  and  $\mathbf{y} = \langle -2, 1 \rangle$ . Then  $\mathbf{x} + \mathbf{y} = \langle 1 - 2, 2 + 1 \rangle = \langle -1, 3 \rangle$ .



Thus we see that to reach  $\mathbf{x} + \mathbf{y}$ , we may first go to  $\mathbf{x}$ , then go in the direction of  $\mathbf{y}$  to get to  $\mathbf{x} + \mathbf{y}$ , or else we may to to  $\mathbf{y}$  first and then go in the direction of  $\mathbf{x}$ . This shows geometrically the algebraic rule called commutativity,  $\mathbf{x} + \mathbf{y} = \mathbf{y} + \mathbf{x}$ .

Let us now observe some direct consequence of our definition, which evidently is just componentwise application of addition in  $\mathbb{R}$ . All the rules for real numbers apply here, where we have *n*-tuples of real numbers, since what we are doing now is just carrying out *n* applications of the same operation at the same time.

**Remark 1.5** Don't be phased by the obviousness of these statements, because their obviousness isn't the point: their obviousness is emphasized here for later purposes. We'll take these properties, so obvious in  $\mathbb{R}^n$ , and use them as the defining characteristics of a new generalization, the abstract concept of a vector space V, in which things will have the same algebraic behavior as vectors in  $\mathbb{R}^n$ . This will cast a wider net, and capture also real polynomials  $\mathbb{R}[x]$ , as well as many function spaces, for example the space of continuous functions  $C(\mathbb{R})$ , or smooth functions  $C^{\infty}(\mathbb{R})$ , etc., in their vector space guise. The space of  $m \times n$  matrices,  $M_{m,n}(\mathbb{R})$ , too, will turn out to satisfy these rules, making *it* a vector space.

**Theorem 1.6 (Properties of Vector Addition)** For all vectors  $\mathbf{x}, \mathbf{y}, \mathbf{z} \in \mathbb{R}^n$ , we have

- (1)  $\mathbf{x} + \mathbf{y} = \mathbf{y} + \mathbf{x}$  (commutativity of addition)
- (2)  $(\mathbf{x} + \mathbf{y}) + \mathbf{z} = \mathbf{x} + (\mathbf{y} + \mathbf{z})$  (associativity of addition)
- (3) The zero vector in  $\mathbb{R}^n$   $\mathbf{0} = \langle 0, \dots, 0 \rangle$  is characterized by  $\mathbf{0} + \mathbf{x} = \mathbf{x} + \mathbf{0} = \mathbf{x}$  for all  $\mathbf{x} \in \mathbb{R}^n$ .
- (4) Every  $\mathbf{x} \in \mathbb{R}^n$  has a negative or additive inverse  $-\mathbf{x} = \langle -x_1, \dots, -x_n \rangle$ which is characterized by  $(-\mathbf{x}) + \mathbf{x} = \mathbf{x} + (-\mathbf{x}) = \mathbf{0}$

**Proof:** We'll prove (1), and leave the others as (slightly tedious) exercises. Let  $\mathbf{x} = \langle x_1, \ldots, x_n \rangle, \mathbf{y} = \langle y_1, \ldots, y_n \rangle \in \mathbb{R}^n$  and follow along:

$$\mathbf{x} + \mathbf{y} = \langle x_1, \dots, x_n \rangle + \langle y_1, \dots, y_n \rangle$$

$$= \langle x_1 + y_1, \dots, x_n + y_n \rangle$$
(our new definition of +)
$$= \langle y_1 + x_1, \dots, y_n + x_n \rangle$$
(commutativity is true in  $\mathbb{R}$ , componentwise)
$$= \mathbf{y} + \mathbf{x}$$

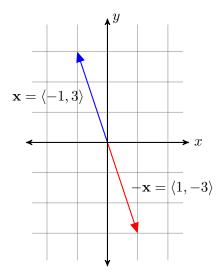
which proves (1).

Now follows a typical math move. Define subtraction to be the addition of negatives.

**Definition 1.7** The subtraction of vectors in  $\mathbb{R}^n$  is now elegantly defined to be addition of negatives:

$$\mathbf{x} - \mathbf{y} := \mathbf{x} + (-\mathbf{y})$$

Geometrically, the negative  $-\mathbf{x}$  of a vector is the reflection of  $\mathbf{x}$  through the origin:



**Remark 1.8** For those of you of a more mathematical bent, we note that, the way we've defined things,  $\mathbb{R}^n$  is an abelian group under addition, +. Actually, if you go down the math rabbit hole far enough you begin to combine algebra with calculus/analysis and topology/geometry in order to create all manner of conceptual chimeras. But the biggest one of these is the general *Lie group*, which is a group with extra topological and smooth structure. You need look no further than  $(\mathbb{R}^n, +)$  to see one, but the group of all invertible matrices, the general linear group  $GL(n, \mathbb{R})$ , provides us with another, and in fact with a whole slew of them: all of its subgroups. Hopefully we'll get to some of this highly interesting material towards the end of the course!

#### 1.2.2 Scalar Multiplication

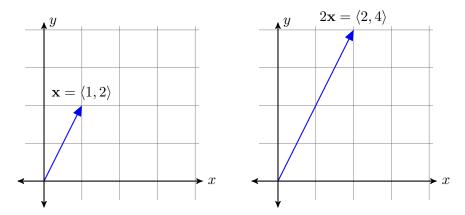
**Definition 1.9** We define scalar multiplication of vectors in  $\mathbb{R}^n$ , by which we mean multiplication of a vector  $\mathbf{x} \in \mathbb{R}^n$  by a real number  $a \in \mathbb{R}$ , componentwise:

$$a\mathbf{x} = a\langle x_1, \dots, x_n \rangle := \langle ax_1, \dots, ax_n \rangle \quad \text{or} \quad a\mathbf{x} = a \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix} := \begin{pmatrix} ax_1 \\ \vdots \\ ax_n \end{pmatrix} \quad \blacksquare$$

The geometric content of scalar multiplication may be seen in the following example: **Example 1.10** Take, say, the vector  $\mathbf{x} = \langle 1, 2 \rangle$  and the real number a = 2. Then, algebraically,

$$a\mathbf{x} = 2\langle 1, 2 \rangle = \langle 2 \cdot 1, 2 \cdot 2 \rangle = \langle 2, 4 \rangle$$

which, geometrically means this:



Thus geometrically scalar multiplication has the effect of scaling the length of the vector  $\mathbf{x}$ .

Immediate properties of scalar multiplication are the following obvious ones, which I leave to you as an exercise to prove.

**Theorem 1.11 (Properties of Scalar Multiplication)** For all  $a, b \in \mathbb{R}$  and all  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ , we have

- (1)  $a(b\mathbf{x}) = (ab)\mathbf{x}$  (associativity of scalar mult.)
- (2)  $(a+b)\mathbf{x} = a\mathbf{x} + b\mathbf{x}$  (distributivity over  $\mathbb{R}$ -addition)
- (3)  $a(\mathbf{x} + \mathbf{y}) = a\mathbf{x} + a\mathbf{y}$  (distributivity over  $\mathbb{R}^n$ -addition)
- (4) 1x = x.

For reasons that must remain obscure for now (having to do with the notion of group actions), we include condition (4) in the immediate foreground (in the theorem above), and keep the next condition separate, not so much because it is a *logical consequence* of the previous theorem, since indeed we can prove it directly from the definition, but because we must keep an eye on our future goal: the abstract vector space. In that case, we won't have 0x defined directly, but will derive its meaning from the above conditions, which will be taken for the definition of scalar multiplication.

**Corollary 1.12** For all  $\mathbf{x} \in \mathbb{R}^n$ , we have  $0\mathbf{x} = \mathbf{0}$ .

**Proof:** Suppose  $\mathbf{x} \in \mathbb{R}^n$ . If we scale by  $0 \in \mathbb{R}$ , we get, straight from our definition,

$$0\mathbf{x} = 0\langle x_1, \dots, x_n \rangle = \langle 0x_1, \dots, 0x_n \rangle = \langle 0, \dots, 0 \rangle = \mathbf{0}$$

since  $0x_i = 0$  for all *i*.

**Remark 1.13** Note, for future purposes, that we could have proved this differently, using only the conditions of the previous theorems: Since the zero vector satisfies  $\mathbf{0} + \mathbf{x} = \mathbf{x}$  for all  $\mathbf{x}$ , and since scalar multiplication is distributive, we get

$$\mathbf{0} + 0\mathbf{x} = 0\mathbf{x} = (0+0)\mathbf{x} = 0\mathbf{x} + 0\mathbf{x}$$

so that, subtracting  $0\mathbf{x}$  from both sides gives  $\mathbf{0} = 0\mathbf{x}$ . This makes no use of the particular way we defined scalar multiplication, it just makes use of its abstract properties (and those of addition).

#### 1.2.3 Standard Coordinate Vectors

We can use addition and scalar multiplicaton of vectors to decompose a given vector  $\mathbf{x} = \langle x_1, \ldots, x_n \rangle$  into its **components**  $x_i$ , as follows:

$$\mathbf{x} = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} x_1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix} + \begin{pmatrix} 0 \\ x_2 \\ 0 \\ \vdots \\ 0 \end{pmatrix} + \dots + \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ x_n \end{pmatrix}$$
(1.8)  
$$= x_1 \begin{pmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix} + x_2 \begin{pmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} + \dots + x_n \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 1 \end{pmatrix}$$

This calls for a definition:

#### Definition 1.14 Define the standard (Cartesian coordinate) basis vectors

$$\mathbf{e}_1 = \begin{pmatrix} 1\\0\\0\\\vdots\\0 \end{pmatrix}, \quad \mathbf{e}_2 = \begin{pmatrix} 0\\1\\0\\\vdots\\0 \end{pmatrix}, \quad \dots, \quad \mathbf{e}_n = \begin{pmatrix} 0\\0\\\vdots\\0\\1 \end{pmatrix}$$

That is,  $\mathbf{e}_i = \langle 0, \dots, 1, \dots, 0 \rangle$  with the 1 in the *i*th slot and 0's everywhere else.

With this in hand, we can nicely rewrite equation (1.8) as

$$\mathbf{x} = \langle x_1, \dots, x_n \rangle = x_1 \mathbf{e}_1 + x_2 \mathbf{e}_2 + \dots + x_n \mathbf{e}_n$$
(1.9)

**Example 1.15** When n = 2, we have special notation, which is more commonly found in physics texts:

$$\begin{array}{rcl}
\mathbf{e}_1 &= \mathbf{i} &= \langle 1, 0 \rangle \\
\mathbf{e}_2 &= \mathbf{j} &= \langle 0, 1 \rangle
\end{array}$$
(1.10)

When n = 3, we also write:

$$\begin{aligned}
\mathbf{e}_1 &= \mathbf{i} = \langle 1, 0, 0 \rangle \\
\mathbf{e}_2 &= \mathbf{j} = \langle 0, 1, 0 \rangle \\
\mathbf{e}_3 &= \mathbf{k} = \langle 0, 0, 1 \rangle
\end{aligned}$$
(1.11)

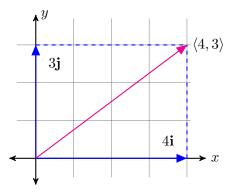
For example,

$$\langle 1, 3, -2 \rangle = 1\mathbf{i} + 3\mathbf{j} - 2\mathbf{k} \tag{1.12}$$

is decomposed into its components. As another example,

$$\langle 4,3\rangle = 4\mathbf{i} + 3\mathbf{j} \tag{1.13}$$

and this can be pictured as follows:



#### **1.3** The Dot and Cross Products

#### 1.3.1 The Dot Product

**Definition 1.16** The **dot product** of two vectors  $\mathbf{x} = \langle x_1, x_2, \dots, x_n \rangle$  and  $\mathbf{y} = \langle y_1, y_2, \dots, y_n \rangle$  in  $\mathbb{R}^n$  is defined by

$$\mathbf{x} \cdot \mathbf{y} = \langle x_1, x_2, \dots, x_n \rangle \cdot \langle y_1, y_2, \dots, y_n \rangle = x_1 y_1 + x_2 y_2 + \dots + x_n y_n$$
(1.14)

or, more concisely, using summation notation,

$$\mathbf{x} \cdot \mathbf{y} = \sum_{i=1}^n x_i y_i$$

**Remark 1.17** We may dot in various ways, in practice, such as dotting the row of a matrix A with a column of a matrix B. Thus, we allow

$$\mathbf{x} \cdot \mathbf{y} = \langle x_1, x_2, \dots, x_n \rangle \cdot \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \sum_{i=1}^n x_i y_i$$

**Example 1.18** Consider the vectors  $\mathbf{x} = \langle 1, 2, -5 \rangle$  and  $\mathbf{y} = \langle -3, 2, 4 \rangle$  in  $\mathbb{R}^3$ . Their dot product is

$$\mathbf{x} \cdot \mathbf{y} = \langle 1, 2, -5 \rangle \cdot \langle -3, 2, 4 \rangle$$
  
=  $1 \cdot (-3) + 2 \cdot 2 + (-5) \cdot 4$   
=  $-19$ 

**Definition 1.19** The **length** (or **magnitude** or **norm**) of a vector  $\mathbf{x}$  in  $\mathbb{R}^n$  will be defined as the square root of the dot product of  $\mathbf{x}$  with itself:

$$\|\mathbf{x}\| = \sqrt{\mathbf{x} \cdot \mathbf{x}} \tag{1.15}$$

Thus,

$$\|\mathbf{x}\| = \sqrt{\sum_{i=1}^{n} x_i^2}$$

and therefore

$$\|\mathbf{x}\|^2 = \sum_{i=1}^n x_i^2 = \mathbf{x} \cdot \mathbf{x}$$

**Example 1.20** The magnitude of the vector  $\mathbf{x} = \langle 4, 1 \rangle \in \mathbb{R}^2$  is

$$\|\langle 4,1\rangle\| = \sqrt{4^2 + 1^2} = \sqrt{17}$$

**Proposition 1.21 (Algebraic Properties of the Dot Product)** Let  $\mathbf{x}$ ,  $\mathbf{y}$ ,  $\mathbf{z}$  be vectors in  $\mathbb{R}^n$  and let c be a real number. Then,

- (1)  $\mathbf{x} \cdot \mathbf{x} = |\mathbf{x}|^2$
- $(2) |c\mathbf{x}| = |c||\mathbf{x}|$
- (3)  $\mathbf{x} \cdot \mathbf{y} = \mathbf{y} \cdot \mathbf{x}$  (commutativity)
- (4)  $\mathbf{x} \cdot (\mathbf{y} + \mathbf{z}) = \mathbf{x} \cdot \mathbf{y} + \mathbf{x} \cdot \mathbf{z}$  (distributivity over addition)
- (5)  $(c\mathbf{x}) \cdot \mathbf{y} = c(\mathbf{x} \cdot \mathbf{y}) = \mathbf{x} \cdot (c\mathbf{y})$  (associativity and commutativity of scalar multiplication and dot multiplication)

(6)  $\mathbf{0} \cdot \mathbf{x} = 0$ 

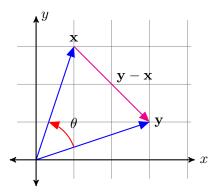
**Proof:** A worthy exercise.

In two and three dimensions, the dot product has a very geometric interpretation:

**Proposition 1.22** Let  $\mathbf{x} = \langle x_1, y_1, z_1 \rangle$  and let  $\mathbf{y} = \langle x_2, y_2, z_2 \rangle$  be two vectors in  $\mathbb{R}^3$ , and let  $\theta$  be the angle between them. Then,

$$\mathbf{x} \cdot \mathbf{y} = \|\mathbf{x}\| \|\mathbf{y}\| \cos \theta \tag{1.16}$$

**Proof:** Consider the triangle formed by the vectors  $\mathbf{x}$ ,  $\mathbf{y}$  and  $\mathbf{y} - \mathbf{x}$ .



By the Law of Cosines

$$\|\mathbf{y} - \mathbf{x}\|^2 = \|\mathbf{x}\|^2 + \|\mathbf{y}\|^2 - 2\|\mathbf{x}\|\|\mathbf{y}\|\cos\theta$$

Using the fact that  $|\mathbf{x}|^2 = \mathbf{x} \cdot \mathbf{x}$ , we can rewrite the above as

$$(\mathbf{y} - \mathbf{x}) \cdot (\mathbf{y} - \mathbf{x}) = \mathbf{x} \cdot \mathbf{x} + \mathbf{y} \cdot \mathbf{y} - 2 \|\mathbf{x}\| \|\mathbf{y}\| \cos \theta$$

Distributing on the left and simplifying, we get

$$\mathbf{y} \cdot \mathbf{y} - 2\mathbf{x} \cdot \mathbf{y} + \mathbf{x} \cdot \mathbf{x} = \mathbf{x} \cdot \mathbf{x} + \mathbf{y} \cdot \mathbf{y} - 2 \|\mathbf{x}\| \|\mathbf{y}\|$$

That is,

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

**Remark 1.23** We observe that if we were clever, we could generalize this to  $\mathbb{R}^n$  by simply *defining* the angle  $\theta$  between  $\mathbf{x}$  and  $\mathbf{y}$  in  $\mathbb{R}^n$  to be

$$\theta := \cos^{-1} \left( \frac{\mathbf{x} \cdot \mathbf{y}}{\|\mathbf{x}\| \|\mathbf{y}\|} \right)$$

which is, of course, what the clever people have already done.

#### 1.3.2 Cross Product

Note that this section requires knowledge of determinants, which is to be found below, in the section on matrices.

The cross product is a *vector* product, meaning that multiplying two vectors this way results in another vector (this is why the dot product is sometimes called the *scalar* product, to distinguish it from this vector product). The cross product is only defined in 3 dimensions, i.e. only on  $\mathbb{R}^{3,1}$ 

Let  $\mathbf{u} = \langle a, b, c \rangle$  and  $\mathbf{v} = \langle d, e, f \rangle$  be two vectors in  $\mathbb{R}^3$ . We define their **cross product** to be the vector gotten by computing the following determinant:

$$\mathbf{u} \times \mathbf{v} = \langle a, b, c \rangle \times \langle d, e, f \rangle = \begin{vmatrix} \mathbf{i} & \mathbf{j} & \mathbf{k} \\ a & b & c \\ d & e & f \end{vmatrix}$$

$$= \mathbf{i} \begin{vmatrix} b & c \\ e & f \end{vmatrix} - \mathbf{j} \begin{vmatrix} a & c \\ d & f \end{vmatrix} + \mathbf{k} \begin{vmatrix} a & b \\ d & e \end{vmatrix}$$
(1.17)

Carrying out this computation to its awful end, we get

$$\mathbf{u} \times \mathbf{v} = (bf - ce)\mathbf{i} - (af - cd)\mathbf{j} + (ae - bd)\mathbf{k} = \langle bf - ce, \ cd - af, \ ae - bd \rangle$$

But it is easier to remember the equation (1.17) in terms of determinants and just perform the rest of the computation by hand in particular cases.

**Example 1.24** Let  $\mathbf{u} = \langle 1, 2, -2 \rangle$  and  $\mathbf{v} = \langle -8, 5, 4 \rangle$ . Then,

$$\mathbf{u} \times \mathbf{v} = \langle 1, 2, -2 \rangle \times \langle -8, 5, 4 \rangle$$

$$= \begin{vmatrix} \mathbf{i} & \mathbf{j} & \mathbf{k} \\ 1 & 2 & -2 \\ -8 & 5 & 4 \end{vmatrix}$$

$$= \mathbf{i} \begin{vmatrix} 2 & -2 \\ 5 & 4 \end{vmatrix} - \mathbf{k} \begin{vmatrix} 1 & -2 \\ -8 & 4 \end{vmatrix} + \mathbf{j} \begin{vmatrix} 1 & 2 \\ -8 & 5 \end{vmatrix}$$

$$= (8+10)\mathbf{i} - (4-16)\mathbf{j} + (5+16)\mathbf{k}$$

$$= \boxed{18\mathbf{i} + 12\mathbf{j} + 21\mathbf{k}} \quad or \quad \boxed{\langle 18, 12, 21 \rangle}$$

**Example 1.25** Let us compute  $\mathbf{i} \times \mathbf{j}$ :

$$\mathbf{i} \times \mathbf{j} = \begin{vmatrix} \mathbf{i} & \mathbf{j} & \mathbf{k} \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{vmatrix} = \mathbf{i} \begin{vmatrix} 0 & 0 \\ 1 & 0 \end{vmatrix} - \mathbf{j} \begin{vmatrix} 1 & 0 \\ 0 & 0 \end{vmatrix} + \begin{vmatrix} 1 & 0 \\ 0 & 1 \end{vmatrix} = 0\mathbf{i} - 0\mathbf{j} + 1\mathbf{k} = \mathbf{k}$$

<sup>&</sup>lt;sup>1</sup>It generalizes to other dimensions only once we switch to the **wedge product** (or **exterior product**) in multilinear algebra. Moving past the algebra we are led to a *differential* type of wedge product in the apparatus of **differential forms**. For further reading on this, see Knapp [2] and Gallier [1] for the algebra, and Munkres [3] for the calculus side.

By similar calculations, which we leave to you, we also have the relations  $\mathbf{j} \times \mathbf{k} = \mathbf{i}$ and  $\mathbf{k} \times \mathbf{i} = \mathbf{j}$ :

$$\mathbf{i} \times \mathbf{j} = \mathbf{k} \mathbf{k} \times \mathbf{i} = \mathbf{j} \mathbf{j} \times \mathbf{k} = \mathbf{i}$$
 (1.18)

Note that the vectors  $\mathbf{i}$ ,  $\mathbf{j}$ ,  $\mathbf{k}$  are cyclically permuted:

$$\mathbf{j}$$
  $\mathbf{k}$  (1.19)

in slots of the equation  $\_ \times \_ = \_$ 

**Proposition 1.26 (Algebraic Properties of the Cross Product)** Let  $\mathbf{x}$ ,  $\mathbf{y}$ ,  $\mathbf{z}$  be vectors in  $\mathbb{R}^3$  and let c be a real number. Then,

- (1)  $\mathbf{x} \times \mathbf{y} = -\mathbf{y} \times \mathbf{x}$  (anti-commutativity)
- (2)  $\begin{aligned} \mathbf{x} \times (\mathbf{y} + \mathbf{z}) &= \mathbf{x} \times \mathbf{y} + \mathbf{x} \times \mathbf{z} \\ (\mathbf{x} + \mathbf{y}) \times \mathbf{z} &= \mathbf{x} \times \mathbf{z} + \mathbf{y} \times \mathbf{z} \end{aligned}$  (distributivity over addition)
- (3)  $(c\mathbf{x}) \times \mathbf{y} = c(\mathbf{x} \times \mathbf{y}) = \mathbf{x} \times (c\mathbf{y})$  (associativity of scalar multiplication and cross multiplication)

**Proof:** Let us prove (1), and leave the rest as easy exercises. Let  $\mathbf{x} = \langle a, b, c \rangle$  and  $\mathbf{y} = \langle d, e, f \rangle$ . Then,

$$\mathbf{y} \times \mathbf{x} = \begin{vmatrix} \mathbf{i} & \mathbf{j} & \mathbf{k} \\ d & e & f \\ a & b & c \end{vmatrix} = \mathbf{i} \begin{vmatrix} e & f \\ b & c \end{vmatrix} - \mathbf{j} \begin{vmatrix} d & f \\ a & c \end{vmatrix} + \begin{vmatrix} d & e \\ a & b \end{vmatrix} = (ce - bf)\mathbf{i} - (cd - af)\mathbf{j} + (bd - ae)\mathbf{k}$$

However, according to the calculation (1.17) above,

$$\mathbf{x} \times \mathbf{y} = (bf - ce)\mathbf{i} - (af - cd)\mathbf{j} + (ae - bd)\mathbf{k} = -\mathbf{y} \times \mathbf{x}$$

**Proposition 1.27** For any vectors  $\mathbf{u}$ ,  $\mathbf{v}$  in  $\mathbb{R}^3$  we have the identity

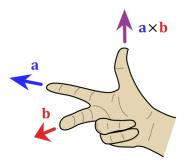
$$\|\mathbf{u} \times \mathbf{v}\| = \|\mathbf{u}\| \|\mathbf{v}\| \sin \theta \tag{1.20}$$

and consequently

$$\mathbf{u} \times \mathbf{v} = \left( \|\mathbf{u}\| \|\mathbf{v}\| \sin \theta \right) \mathbf{n}$$
(1.21)

where  $\theta$  is the angle between the vectors and  $\mathbf{n} = \frac{\mathbf{u} \times \mathbf{v}}{\|\mathbf{u} \times \mathbf{v}\|}$  is the unit vector in the direction of  $\mathbf{u} \times \mathbf{v}$ , determined by the **right-hand rule**, illustrated in the following diagram,<sup>2</sup>

<sup>&</sup>lt;sup>2</sup>Which I got from the Wikipedia page on the cross product, http://en.wikipedia.org/wiki/Cross\_product.



**Proof:** Let  $\mathbf{u} = \langle a, b, c \rangle$  and  $\mathbf{v} = \langle d, e, f \rangle$ . By the calculation (1.17) we have that  $\mathbf{u} \times \mathbf{v} = \langle bf - ce, cd - af, ae - bd \rangle$ , and consequently

$$\begin{split} \|\mathbf{u}\|^2 \|\mathbf{v}\|^2 \sin^2 \theta &= \|\mathbf{u}\|^2 \|\mathbf{v}\|^2 (1 - \cos^2 \theta) \\ &= \|\mathbf{u}\|^2 \|\mathbf{v}\|^2 - \|\mathbf{u}\|^2 \|\mathbf{v}\|^2 \cos^2 \theta \\ &= \|\mathbf{u}\|^2 \|\mathbf{v}\|^2 - (\mathbf{u} \cdot \mathbf{v})^2 \\ &= (a^2 + b^2 + c^2)(d^2 + e^2 + f^2) - (ad + be + cf)^2 \\ &= (a^2d^2 + b^2e^2 + c^2f^2 + b^2f^2 + c^2e^2 + c^2d^2 + a^2f^2 + a^2e^2 + b^2d^2) \\ &- (a^2d^2 + b^2e^2 + c^2f^2 + 2bcef + 2acdf + 2abde) \\ &= (b^2f^2 - 2bcef + c^2e^2) + (c^2d^2 - 2acdf + a^2f^2) + (a^2e^2 - 2abde + b^2d^2) \\ &+ (a^2d^2 + b^2e^2 + c^2f^2) - (a^2d^2 + b^2e^2 + c^2f^2) \\ &= (bf - ce)^2 + (cd - af)^2 + (ae - bd)^2 \\ &= \langle bf - ce, \ cd - af, \ ae - bd \rangle \cdot \langle bf - ce, \ cd - af, \ ae - bd \rangle \\ &= \|\mathbf{u} \times \mathbf{v}\|^2 \end{split}$$

Taking the square root gives the result.

#### 1.3.3 Interaction Between the Dot and Cross Products

**Proposition 1.28** Let  $\mathbf{a} = \langle a_1, a_2, a_3 \rangle$ ,  $\mathbf{b} = \langle b_1, b_2, b_3 \rangle$ ,  $\mathbf{c} = \langle c_1, c_2, c_3 \rangle$  be vectors in  $\mathbb{R}^3$ . Then,

(1) 
$$\begin{aligned} \mathbf{a} \times (\mathbf{b} \times \mathbf{c}) &= (\mathbf{a} \cdot \mathbf{c})\mathbf{b} - (\mathbf{a} \cdot \mathbf{b})\mathbf{c} \\ (\mathbf{a} \times \mathbf{b}) \times \mathbf{c} &= (\mathbf{a} \cdot \mathbf{c})\mathbf{b} - (\mathbf{c} \cdot \mathbf{b})\mathbf{a} \end{aligned}$$
(vector triple product)  
(2) 
$$(\mathbf{a} \times \mathbf{b}) \cdot \mathbf{c} &= (\mathbf{c} \times \mathbf{a}) \cdot \mathbf{b} = (\mathbf{b} \times \mathbf{c}) \cdot \mathbf{a} = \begin{vmatrix} a_1 & a_2 & a_3 \\ b_1 & b_2 & b_3 \\ c_1 & c_2 & c_3 \end{vmatrix} = \mathbf{a} \cdot (\mathbf{b} \times \mathbf{c}) = \mathbf{c} \cdot (\mathbf{a} \times \mathbf{b}) = \mathbf{b} \cdot (\mathbf{c} \times \mathbf{a})$$
(scalar triple product)  
(3) 
$$(\mathbf{a} \times \mathbf{b}) \times \mathbf{c} + (\mathbf{c} \times \mathbf{a}) \times \mathbf{b} + (\mathbf{b} \times \mathbf{c}) \times \mathbf{a} = \mathbf{0}$$
(Jacobi identity)

**Proof:** (1) This is a direct computation:

$$\begin{aligned} \mathbf{a} \times (\mathbf{b} \times \mathbf{c}) &= \begin{vmatrix} \mathbf{i} & \mathbf{j} & \mathbf{k} \\ a_1 & a_2 & a_3 \\ |b_2 & b_3| & -|b_1 & b_3| & |b_1 & b_2| \\ c_1 & c_3| & |b_1 & b_3| \\ c_2 & c_3| & -a_1 \begin{vmatrix} b_1 & b_2 \\ c_1 & c_2 \end{vmatrix} , \\ & a_3 \begin{vmatrix} b_2 & b_3 \\ c_2 & c_3 \end{vmatrix} - a_1 \begin{vmatrix} b_1 & b_2 \\ c_1 & c_2 \end{vmatrix} , \\ & -a_1 \begin{vmatrix} b_1 & b_3 \\ c_2 & c_3 \end{vmatrix} - a_2 \begin{vmatrix} b_2 & b_3 \\ c_2 & c_3 \end{vmatrix} \right) \end{aligned}$$

$$= \langle a_2(b_1c_2 - b_2c_1) + a_3(b_1c_3 - b_3c_1), \\ & a_3(b_2c_3 - b_3c_2) - a_1(b_1c_2 - b_2c_1), \\ & -a_1(b_1c_3 - b_3c_1) - a_2(b_2c_3 - b_3c_2) \rangle \end{aligned}$$

$$= \langle a_2b_1c_2 - a_2b_2c_1 + a_3b_1c_3 - a_3b_3c_1, \\ & a_3b_2c_3 - a_3b_3c_2 - a_1b_1c_2 + a_1b_2c_1, \\ & -a_1b_1c_3 + a_1b_3c_1 - a_2b_2c_3 + a_2b_3c_2 \rangle + \langle a_1b_1c_1, a_2b_2c_2, a_3b_3c_3 \rangle - \langle a_1b_1c_1, a_2b_2c_2, a_3b_3c_3 \rangle - \langle (a_1c_1 + a_3c_3)b_2 - (a_1b_1 + a_3b_3)c_2, \\ & (a_1c_1 + a_2c_2)b_3 - (a_1b_1 + a_2b_2 + a_3b_3)c_1, \\ & (a_1c_1 + a_2c_2 + a_3c_3)b_1 - (a_1b_1 + a_2b_2 + a_3b_3)c_1, \\ & (a_1c_1 + a_2c_2 + a_3c_3)b_2 - (a_1b_1 + a_2b_2 + a_3b_3)c_2, \end{vmatrix}$$

$$(a_1c_1 + a_2c_2 + a_3c_3)b_3 - (a_1b_1 + a_2b_2 + a_3b_3)c_3$$

$$= \langle (\mathbf{a} \cdot \mathbf{c})b_1 - (\mathbf{a} \cdot \mathbf{b})c_1, (\mathbf{a} \cdot \mathbf{c})b_2 - (\mathbf{a} \cdot \mathbf{b})c_2, (\mathbf{a} \cdot \mathbf{c})b_3 - (\mathbf{a} \cdot \mathbf{b})c_3 \rangle$$
$$= (\mathbf{a} \cdot \mathbf{c})\mathbf{b} - (\mathbf{a} \cdot \mathbf{b})\mathbf{c}$$

The other expression in (1) follows from this one and the anti-commutativity of the cross product:  $-(\mathbf{a} \times \mathbf{b}) \times \mathbf{c} = \mathbf{c} \times (\mathbf{a} \times \mathbf{b}) = (\mathbf{c} \cdot \mathbf{b})\mathbf{a} - (\mathbf{c} \cdot \mathbf{a})\mathbf{b}$  so that  $(\mathbf{a} \times \mathbf{b}) \times \mathbf{c} = (\mathbf{a} \cdot \mathbf{c})\mathbf{b} - (\mathbf{c} \cdot \mathbf{b})\mathbf{a}$ .

For (2), we simply compute, using some basic facts about determinants:

$$(\mathbf{a} \times \mathbf{b}) \cdot \mathbf{c} = \left\langle \begin{vmatrix} a_2 & a_3 \\ b_2 & b_3 \end{vmatrix}, - \begin{vmatrix} a_1 & a_3 \\ b_1 & b_3 \end{vmatrix}, \begin{vmatrix} a_1 & a_2 \\ b_1 & b_2 \end{vmatrix} \right\rangle \cdot \langle c_1, c_2, c_3 \rangle$$

$$= \left| \begin{vmatrix} a_2 & a_3 \\ b_2 & b_3 \end{vmatrix} c_1 - \left| \begin{vmatrix} a_1 & a_3 \\ b_1 & b_3 \end{vmatrix} c_2 + \left| \begin{vmatrix} a_1 & a_2 \\ b_1 & b_2 \end{vmatrix} c_3$$

$$= \left| \begin{vmatrix} a_1 & a_2 & a_3 \\ b_1 & b_2 & b_3 \\ c_1 & c_2 & c_3 \end{vmatrix}$$

$$= \left| \begin{vmatrix} c_1 & c_2 & c_3 \\ a_1 & a_2 & a_3 \\ b_1 & b_2 & b_3 \end{vmatrix} = (\mathbf{c} \times \mathbf{a}) \cdot \mathbf{b} = \mathbf{b} \cdot (\mathbf{c} \times \mathbf{a})$$

$$= \left| \begin{vmatrix} b_1 & b_2 & b_3 \\ c_1 & c_2 & c_3 \\ a_1 & a_2 & a_3 \end{vmatrix} = (\mathbf{b} \times \mathbf{c}) \cdot \mathbf{a} = \mathbf{a} \cdot (\mathbf{b} \times \mathbf{c})$$

$$= \mathbf{c} \cdot (\mathbf{a} \times \mathbf{b})$$

since each of the other two determinants is obtained from the first by 2 row interchanges, which are equal to  $(-1)^2$  times the first.

The Jacobi identity (3) follows from the vector triple product:  $(\mathbf{a} \times \mathbf{b}) \times \mathbf{c} + (\mathbf{c} \times \mathbf{a}) \times \mathbf{b} + (\mathbf{b} \times \mathbf{c}) \times \mathbf{a} = (\mathbf{a} \cdot \mathbf{c})\mathbf{b} - (\mathbf{a} \cdot \mathbf{b})\mathbf{c} + (\mathbf{c} \cdot \mathbf{b})\mathbf{a} - (\mathbf{c} \cdot \mathbf{a})\mathbf{b} + (\mathbf{b} \cdot \mathbf{a})\mathbf{c} - (\mathbf{b} \cdot \mathbf{c})\mathbf{a} = \mathbf{0}.$ 

#### 1.3.4 Geometric Properties of the Dot and Cross Products

The formulas

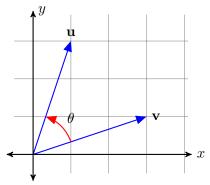
$$\mathbf{u} \cdot \mathbf{v} = \|\mathbf{u}\| \|\mathbf{v}\| \cos \theta \tag{1.22}$$

$$\|\mathbf{u} \times \mathbf{v}\| = \|\mathbf{u}\| \|\mathbf{v}\| \sin \theta \qquad (1.23)$$

for all vectors  $\mathbf{u}$  and  $\mathbf{v}$  in  $\mathbb{R}^3$  forming an acute angle  $\theta$ , already contain significant geometric information. The purely algebraic definition of  $\mathbf{u} \cdot \mathbf{v} = u_1 v_1 + u_2 v_2 + u_3 v_3$ , which a priori doesn't say anything about angles and orthogonality, turns out to in fact give precisely that information. Indeed, we can use purely algebraic information about  $\mathbf{u}$  and  $\mathbf{v}$ , namely their magnitudes and dot product, to gain the important geometric information about the acute angle they form:

$$\theta = \cos^{-1} \left( \frac{\mathbf{u} \cdot \mathbf{v}}{\|\mathbf{u}\| \|\mathbf{v}\|} \right) \tag{1.24}$$

(provided, of course, that neither vector is the zero vector  $\mathbf{0} = \langle 0, 0, 0 \rangle$ , else we'd be dividing by 0).



This fact motivates the following definition. We say two vectors  $\mathbf{u}$  and  $\mathbf{v}$  are **orthogonal** or **perpendicular** if  $\mathbf{u} \cdot \mathbf{v} = 0$ , and we denote this by

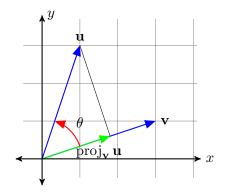
$$\mathbf{u} \perp \mathbf{v} \tag{1.25}$$

From equation (1.22) we immediately get that

$$\mathbf{u} \perp \mathbf{v} \iff \cos \theta = 0 \iff \theta = \frac{\pi}{2}$$
 (1.26)

Next, consider the projection of the vector  $\mathbf{u}$  onto the vector  $\mathbf{v}$ , that is, drop a

perpendicular from the arrowhead of  $\mathbf{u}$  onto the line containing  $\mathbf{v}$ ,



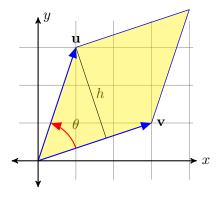
Observe that the length of the projection is clearly

$$\operatorname{comp}_{\mathbf{v}} \mathbf{u} = \|\operatorname{proj}_{\mathbf{v}} \mathbf{u}\| = \|\mathbf{u}\| \cos \theta = \|\mathbf{u}\| \frac{\|\mathbf{v}\|}{\|\mathbf{v}\|} \cos \theta = \frac{\mathbf{u} \cdot \mathbf{v}}{\|\mathbf{v}\|}$$
(1.27)

Therefore, if we give it a direction, namely the unit direction  $\frac{\mathbf{v}}{\|\mathbf{v}\|}$  of  $\mathbf{v},$  we get

$$\operatorname{proj}_{\mathbf{v}} \mathbf{u} = (\|\mathbf{u}\| \cos \theta) \frac{\mathbf{v}}{\|\mathbf{v}\|} = \frac{\mathbf{u} \cdot \mathbf{v}}{\|\mathbf{v}\|^2} \mathbf{v}$$
(1.28)

Next, consider the parallelogram formed by the vectors  $\mathbf{u}$  and  $\mathbf{v}$ :



We know that its area is the length of its base times its height,

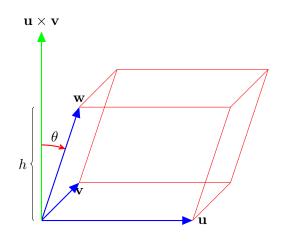
$$A = bh$$

Now,  $b = |\mathbf{v}|$  and  $h = |\mathbf{u}| \sin \theta$ , so by equation

$$A = bh = \|\mathbf{v}\| \|\mathbf{u}\| \sin \theta = \|\mathbf{u} \times \mathbf{v}\|$$
(1.29)

i.e. the area of the parallelogram determined by  ${\bf u}$  and  ${\bf v}$  is the length of their cross product!

Now consider a **parallelepiped** spanned by three vectors  $\mathbf{u}$ ,  $\mathbf{v}$ ,  $\mathbf{w}$ , the 3-dimensional analog of the parallelogram, a rectangular solid whose opposite sides are all parallel.



The volume is the area of the parallelogram spanned by  $\mathbf{u}$  and  $\mathbf{v}$  times the height h,

$$V = Ah = \|\mathbf{u} \times \mathbf{v}\|h$$

But note that h is the length of the projection of  $\mathbf{w}$  onto  $\mathbf{u} \times \mathbf{v}$ ,

$$h = \|\operatorname{comp}_{\mathbf{u} \times \mathbf{v}} \mathbf{w}\| = \frac{|\mathbf{w} \cdot (\mathbf{u} \times \mathbf{v})|}{\|\mathbf{u} \times \mathbf{v}\|} = \left|\mathbf{w} \cdot \left(\frac{\mathbf{u} \times \mathbf{v}}{\|\mathbf{u} \times \mathbf{v}\|}\right)\right| = \|\mathbf{w}\||\cos\theta|$$

Hence,

$$V = Ah = \|\mathbf{u} \times \mathbf{v}\| \frac{|\mathbf{w} \cdot (\mathbf{u} \times \mathbf{v})|}{\|\mathbf{u} \times \mathbf{v}\|} = |(\mathbf{u} \times \mathbf{v}) \cdot \mathbf{w}|$$
(1.30)

I.e., the volume V is equal to the absolute value of the scalar triple product of  $\mathbf{u}$ ,  $\mathbf{v}$ and  $\mathbf{w}$ , which, by our formulas for the scalar triple product from Proposition 1.28, can be computed using the determinant: if  $\mathbf{u} = \langle u_1, u_2, u_3 \rangle$ ,  $\mathbf{v} = \langle v_1, v_2, v_3 \rangle$  and  $\mathbf{w} = \langle w_1, w_2, w_3 \rangle$ , then

$V =  (\mathbf{u} \times \mathbf{v}) \cdot \mathbf{w}  = \text{absolute value of}$	$v_1$	$v_2$	$v_3$	(1.31)
	$w_1$	$w_2$	$w_3$	

## 2 Appendix: The Relationship Between Points and Vectors the Displacement Vector

Let  $O = (0, ..., 0) \in \mathbb{R}^n$  be the origin, thought of as a point. Given any two points  $P = (x_1, ..., x_n)$  and  $Q = (y_1, ..., y_n)$  in  $\mathbb{R}^n$ , define associated vectors, which we denote

$$\overrightarrow{OP} := \langle x_1, \dots, x_n \rangle, \quad \overrightarrow{OQ} := \langle y_1, \dots, y_n \rangle$$

Then, the **displacement vector** from P to Q is defined as

$$\overrightarrow{PQ} = \overrightarrow{OQ} - \overrightarrow{OP}$$

$$= \langle y_1, \dots, y_n \rangle - \langle x_1, \dots, x_n \rangle$$

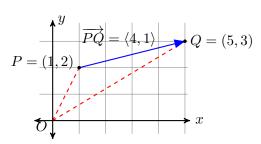
$$= \langle y_1 - x_1, \dots, y_n - x_n \rangle$$
(2.1)

We picture the displacement vector  $\overrightarrow{PQ}$  as emanating from the point P and ending in an arrow at the point Q (even though it always, strictly speaking, emanates from the origin to its endpoint).

**Example 2.1** Let us look at the case of  $\mathbb{R}^2$ . Suppose P = (1,2) and Q = (5,3). Then,

$$\overrightarrow{PQ} = \overrightarrow{OQ} - \overrightarrow{OP} = \langle 5, 3 \rangle - \langle 1, 2 \rangle = \langle 5 - 1, 3 - 2 \rangle = \langle 4, 1 \rangle$$
(2.2)

and the picture is this:



**Remark 2.2** In fact,  $\overrightarrow{PQ}$  should be pictured as emanating from the origin, but we want to think of  $\overrightarrow{PQ}$  as emanating from P. We should, then, if we were being rigorous, think of  $\overrightarrow{PQ}$  as lying in a copy of  $\mathbb{R}^n$  sitting above our position space  $\mathbb{R}^n$  at the point P, that is we should think of  $\overrightarrow{PQ}$  as lying in the set  $\{P\} \times \mathbb{R}^n = \{(P, \mathbf{x}) | \mathbf{x} = \langle x_1, \ldots, x_n \rangle\}$ , and thus

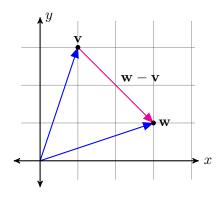
$$\overrightarrow{PQ} = (P, \overrightarrow{OQ} - \overrightarrow{OP})$$

For example, if P = (1, 2) and Q = (5, 3), then

$$\overrightarrow{PQ} = \left( (1,2), \ \langle 4,1 \rangle \right)$$

We will not nit-pick here, and we will simply conflate points and vectors in the strict sense, but we will *picture* vectors as emanating from points in the underlying position space.

Now suppose we are considering not two points P and Q, but two vectors  $\mathbf{v}$  and  $\mathbf{w}$ . Then we can consider the **displacement vector** from  $\mathbf{v}$  to  $\mathbf{w}$ . This is, in fact  $\mathbf{w} - \mathbf{v}$ , which is simply due to the fact that  $\mathbf{w} = \mathbf{v} + (\mathbf{w} - \mathbf{v})$ :



This of course harmonizes with our previous definition,  $\overrightarrow{PQ} = \overrightarrow{OQ} - \overrightarrow{OP}$ . We subtract our starting position vector from our ending position vector in both cases.

The formula for the **distance between two points**  $P = (x_1, \ldots, x_n)$  and  $Q = (y_1, \ldots, y_n)$  is the formula gotten from a generalized Pythagorean theorem,

$$d(P,Q) = d\Big((x_1,\ldots,x_n), (y_1,\ldots,y_n)\Big) = \sqrt{\sum_{i=1}^n (y_i - x_i)^2}$$
(2.3)

In the cases n = 2 and n = 3, this is literally the Pythagorean theorem. For n > 3 it's simply a definition which in a way takes the Pythagorean theorem as an axiom.

What is the relationship between the distance formula and the length of a vector? It is that the length of the displacement vector  $\overrightarrow{PQ}$  is precisely the distance between P and Q:

$$\begin{aligned} \|\overrightarrow{PQ}\| &= \sqrt{\overrightarrow{PQ} \cdot \overrightarrow{PQ}} \\ &= \sqrt{(\overrightarrow{Q} - \overrightarrow{P}) \cdot (\overrightarrow{Q} - \overrightarrow{P})} \\ &= \sqrt{\langle y_1 - x_1, \dots, y_n - x_n \rangle \cdot \langle y_1 - x_1, \dots, y_n - x_n \rangle} \\ &= \sqrt{\sum_{i=1}^n (y_i - x_i)^2} \\ &= d(P, Q) \end{aligned}$$

## References

- [1] Gallier, J. Notes on Differential Geometry, online notes at http://www.cis. upenn.edu/~jean/gbooks/manif.html, Version of August 2013.
- [2] Knapp, A.W., Basic Algebra, Birkh auser, 2000.
- [3] Munkres, J.R., Analysis On Manifolds, Westview Press, 1997.