

Vectors

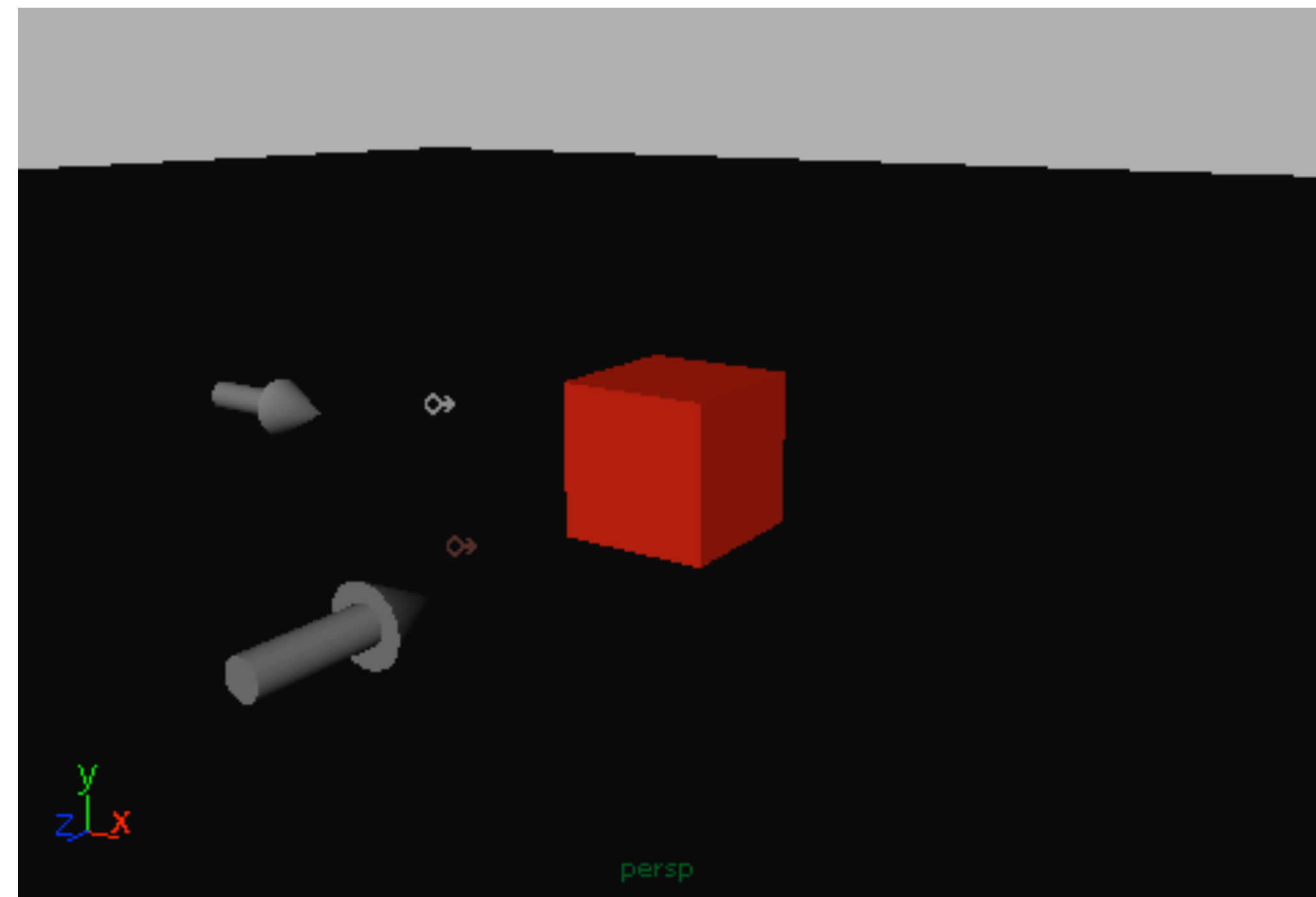
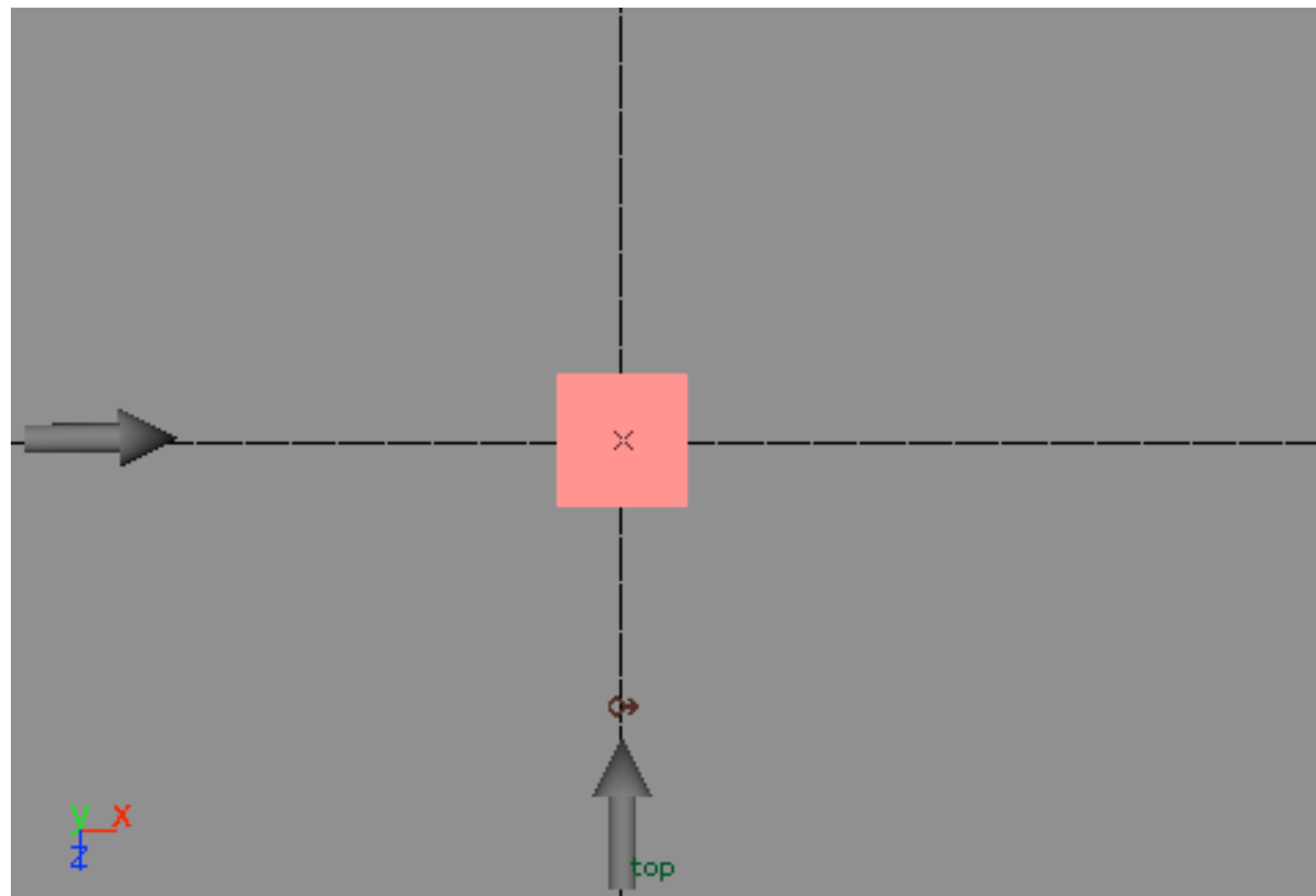
Scalars

- We often employ a single number to represent quantities that we use in our daily lives such as weight, height etc.
- The magnitude of this number depends on our age and whether we use metric or imperial units.
- Such quantities are called **scalars**.
- In computer graphics scalar quantities include height, width, depth, brightness, number of frames, etc.

Vectors

- There are some things that require more than one number to represent them: wind, force, velocity and sound.
- These cannot be represented accurately by a single number.
- For example, wind has a magnitude and a direction.
- The force we use to lift an object also has a value and a direction.
- The velocity of a moving object is measured in terms of its speed (Km per hour) and a direction such as north west.
- Sound, too, has intensity and a direction.
- These quantities are called vectors.

Vector Example



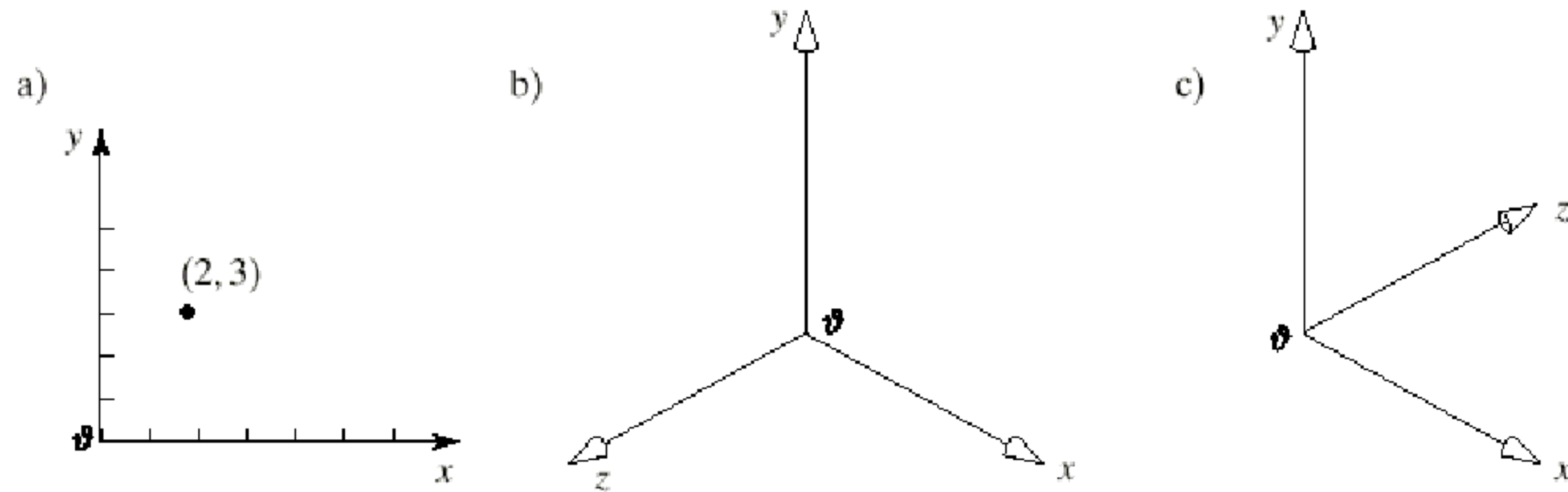
Gravity and Wind



Vectors in scripting

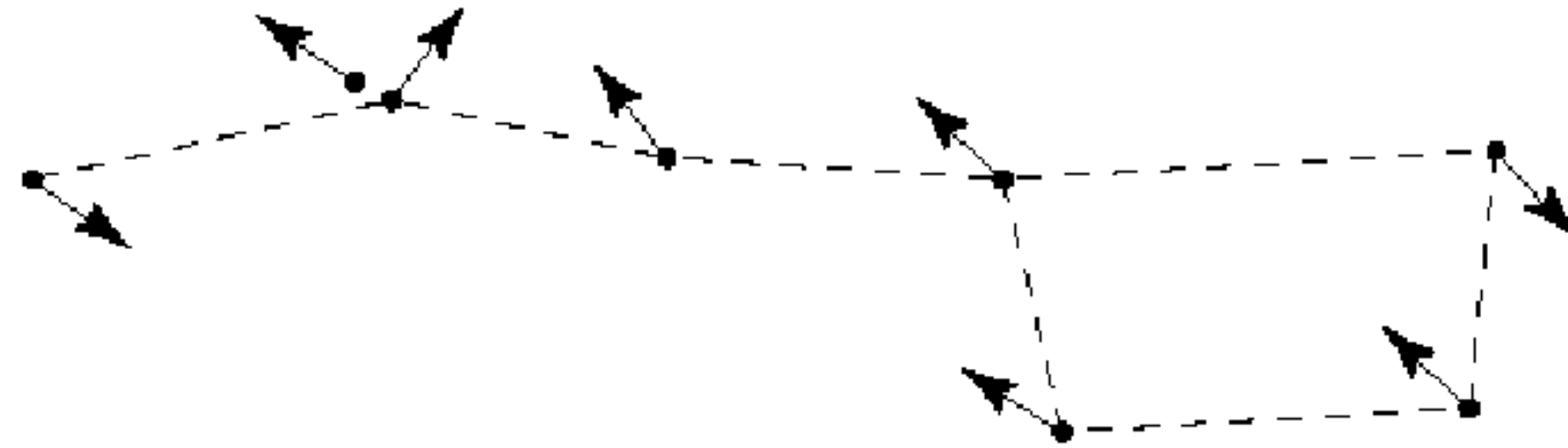
- Most programming languages have no direct support for Vectors and Matrices.
- Usually we either write our own system or use a 3rd party one.
- As Vectors and Matrices are fundamental to 3D graphics most graphics package API give use their own system for doing mathematics with them.
- Additionally to this the numpy system (<http://www.scipy.org/>) gives us the ability to create Vectors (`array()`) and matrices (`matrix()`)

Introduction to Vectors



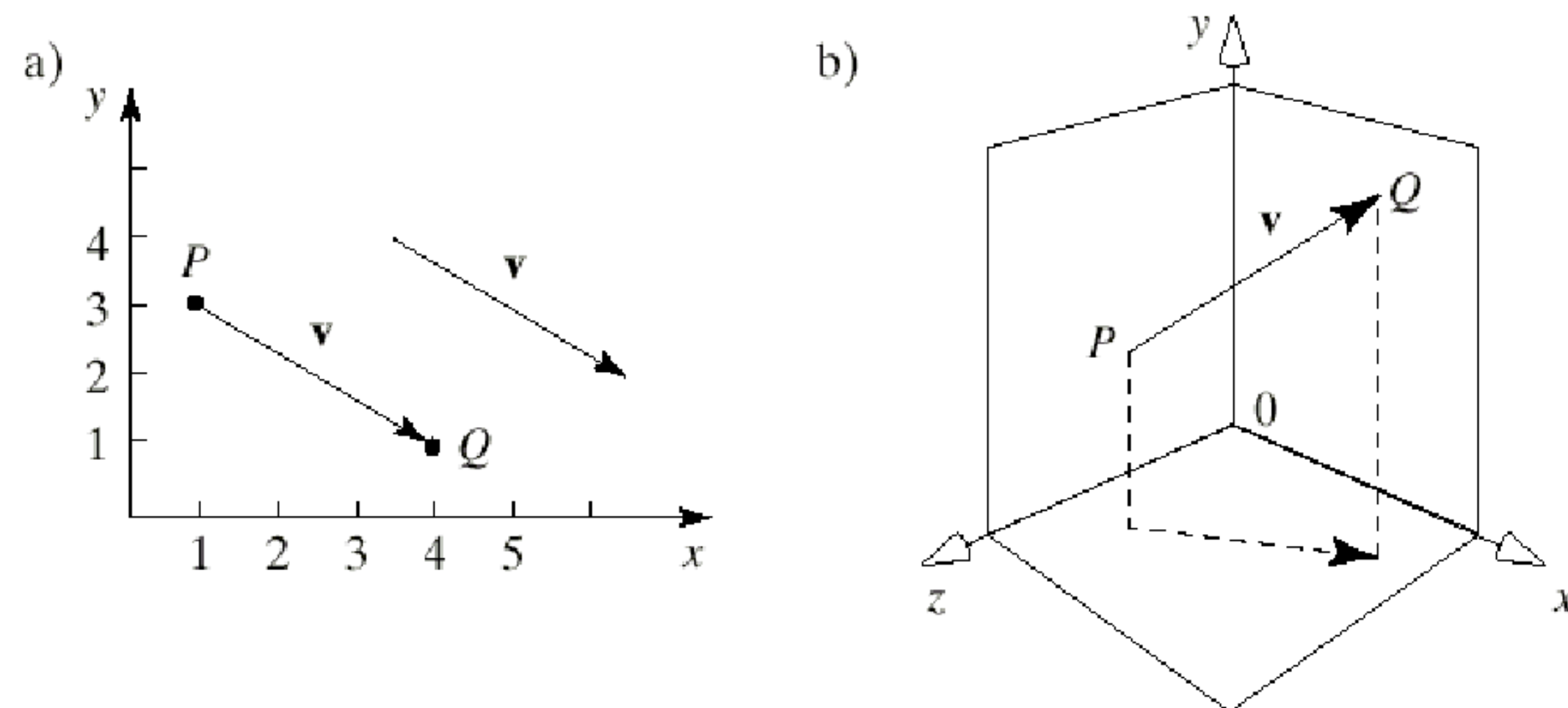
- All points and vectors we use are defined relative to some co-ordinate system
- Each system has an origin \mathcal{O} and some axis emanating from \mathcal{O}
- a) shows a 2D system whilst b) shows a right handed system and c) a left handed system
- In a right handed system, if you rotate your right hand around the Z axis by sweeping from the positive x-axis around to the positive y-axis your thumb points along the positive z axis.
- Right handed systems are used for setting up model views
- Left handed are used for setting up cameras

Simple Vectors



- Vector arithmetic provides a unified way to express geometric ideas algebraically
- In graphics we use 2,3 and 4 dimensional vectors however most operations are applicable to all kinds of vectors
- Viewed geometrically, vectors are objects having **length** and **direction**
- They represent various physical entities such as force, displacement, and velocity
- They are often drawn as arrows of a certain length pointing in a certain direction.
- A good analogy is to think of a vector as a displacement from one point to another

More Vectors



- Fig a) shows in a 2D co-ordinate system two points $P=(1,3)$ and $Q=(4,1)$
- The displacement from P to Q is a vector \mathbf{v} having components $(3,-2)$, calculated by subtracting the co-ordinates of the points individually.
- Because a vector is a displacement, it has a size and a direction, but no inherent location.
- Fig b) shows the corresponding situation in 3 dimensions : \mathbf{v} is the vector from point P to point Q.

Vectors

- The difference between two points is a vector $\mathbf{v} = \mathbf{Q} - \mathbf{P}$
- Turning this around, we also say that a point \mathbf{Q} is formed by displacing point \mathbf{P} by vector \mathbf{v} ; we say the \mathbf{v} “offsets” \mathbf{P} to form \mathbf{Q}
- Algebraically, \mathbf{Q} is then the sum: $\mathbf{Q} = \mathbf{P} + \mathbf{v}$ also the sum of a point and a vector is a point $\mathbf{P} + \mathbf{v} = \mathbf{Q}$
- Vectors can be represented as a list of components, i.e. an n -dimensional vector is given by an n -tuple $\mathbf{w} = [w_1 \ w_2 \ \dots \ w_n]$
- For now we will be using 2D and 3D vectors such as $r = [3.4 \ -7.78]$ and $t = [33 \ 142.7 \ 89.1]$ however later we will represent these as a column matrix as shown below

$$r = \begin{bmatrix} 3.4 \\ -7.78 \end{bmatrix} \text{ and } t = \begin{bmatrix} 33 \\ 142.7 \\ 89.1 \end{bmatrix}$$

Operations With Vectors

- Vectors permit two fundamental operations;
 - Addition
 - Multiplication with Scalars
- The following example assumes **a** and **b** are two vectors, and *s* is a scalar

$$\text{If } \mathbf{a} = \begin{bmatrix} 2 & 5 & 6 \end{bmatrix} \text{ and } \mathbf{b} = \begin{bmatrix} -2 & 7 & 1 \end{bmatrix}$$

we can form two vectors :-

$$\mathbf{a} + \mathbf{b} = \begin{bmatrix} 0 & 12 & 7 \end{bmatrix} \text{ and } 6\mathbf{a} = \begin{bmatrix} 12 & 30 & 36 \end{bmatrix}$$

Vectors and Scalars

- A scalar is a single number e.g. 7
- A vector is a group of e.g. [4,5,3]
- Scalar and Vector addition

$$2 + 5 = 7 \text{ and } [2 \ 3 \ 5] + [2 \ 7 \ 2] = [4 \ 10 \ 7]$$

- Scalar product and scalar product (dot product) of two vectors

$$7 \times 8 = 56 \text{ and } [1 \ 2 \ 3] \cdot [2 \ 4 \ 6] = [1 \times 2 + 2 \times 4 + 3 \times 6] = 28$$

VectorScalar.py

```
1  #!/usr/bin/python
2  from math import *
3  from numpy import *
4
5  def inputVector() :
6      d=raw_input("enter_vector_x,y,z...n_>")
7      f=d.split(",")
8      Vector=array(f,dtype=float32)
9      return Vector
10
11
12
13 Vector=inputVector()
14 s=float(raw_input("enter_a_scalar_>"))
15 print Vector , "_*__", s, "=", Vector * s
```

```
[jmacey@neuromancer:Lecture4]$ ./VectorScalar.py
```

```
enter vector x,y,z...n >2,4,5
```

```
enter a scalar >0.5
```

```
[ 2.  4.  5.] * 0.5 = [ 1.  2.  2.5]
```

```
[jmacey@neuromancer:Lecture4]$ ./VectorScalar.py
```

```
enter vector x,y,z...n >4,7,2,9,33
```

```
enter a scalar >2.6
```

```
[ 4.  7.  2.  9. 33.] * 2.6 = [ 10.39999962  18.19999886  5.19999981  23.39999962  85.79999542]
```

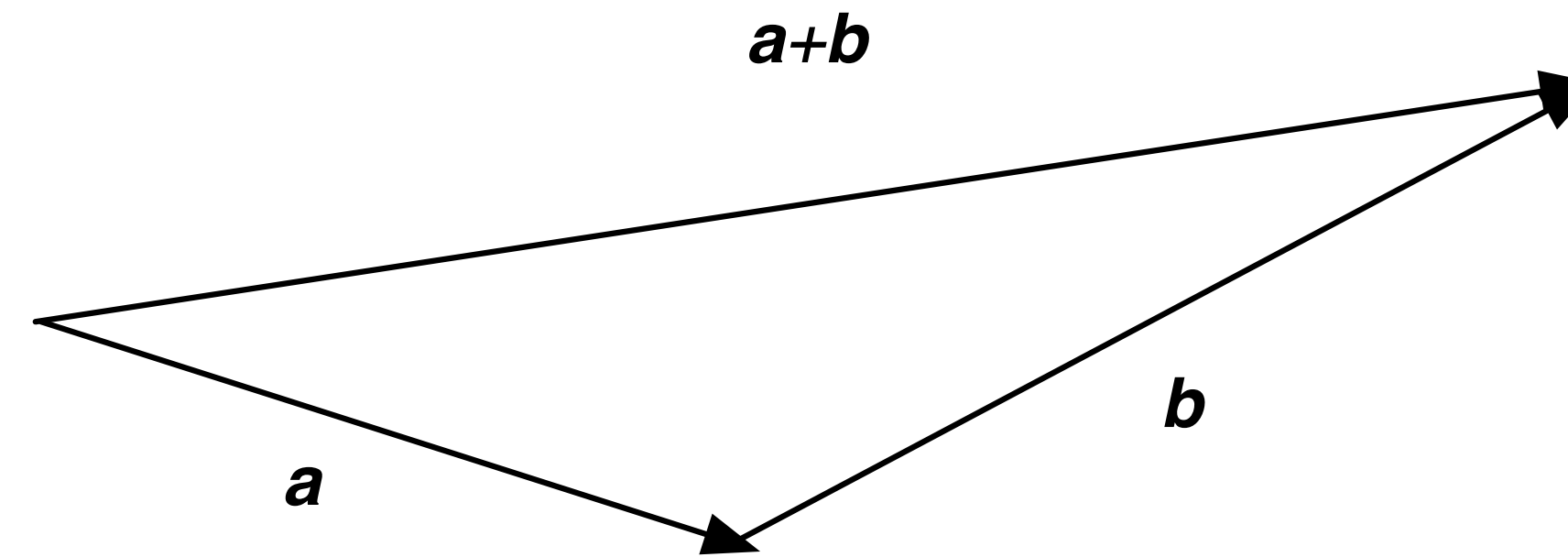
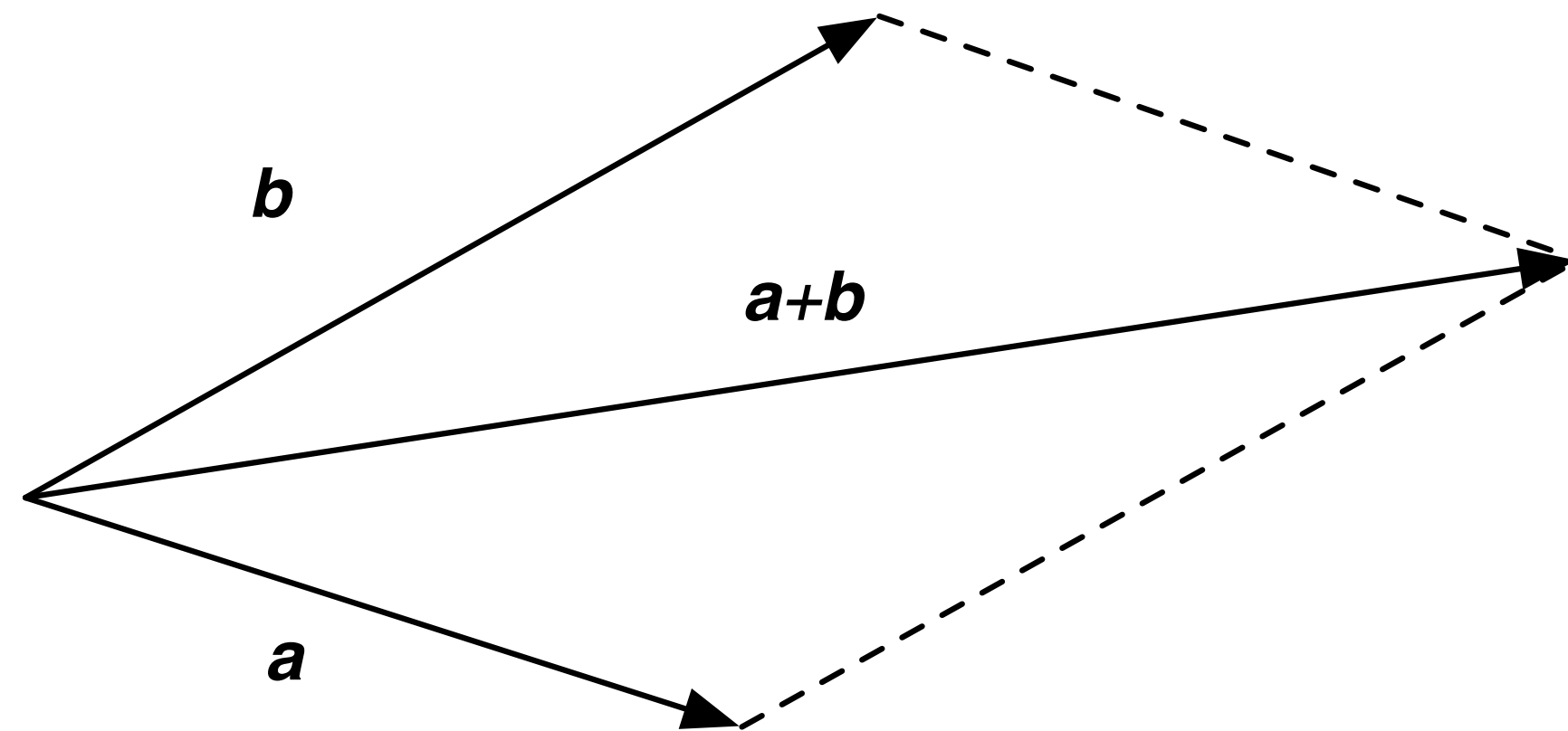
VectorScalar.py

VectorMultiplication.py

```
1  #!/usr/bin/python
2  from math import *
3  from numpy import *
4
5  def inputVector() :
6      d=raw_input("enter_vector_x,y,z_>")
7      f=d.split(",")
8      Vector=array(f, dtype=float32)
9      return Vector
10
11
12 Vector1=inputVector()
13 Vector2=inputVector()
14
15 print Vector1 , ". .", Vector2 , "= .", dot (Vector1,Vector2)
```

```
[jmacey@neuromancer:Lecture4]$ ./VectorMultiplication.py
enter vector x,y,z >2,3,4
enter vector x,y,z >1,2,3
[ 2.  3.  4.] . [ 1.  2.  3.] = 20.0
[jmacey@neuromancer:Lecture4]$ ./VectorMultiplication.py
enter vector x,y,z >2.4,0.2,10
enter vector x,y,z >2.5,0.9,1.5
[ 2.4000001  0.2  10. ] . [ 2.5  0.89999998  1.5 ] = 21.18
```

Vector Addition



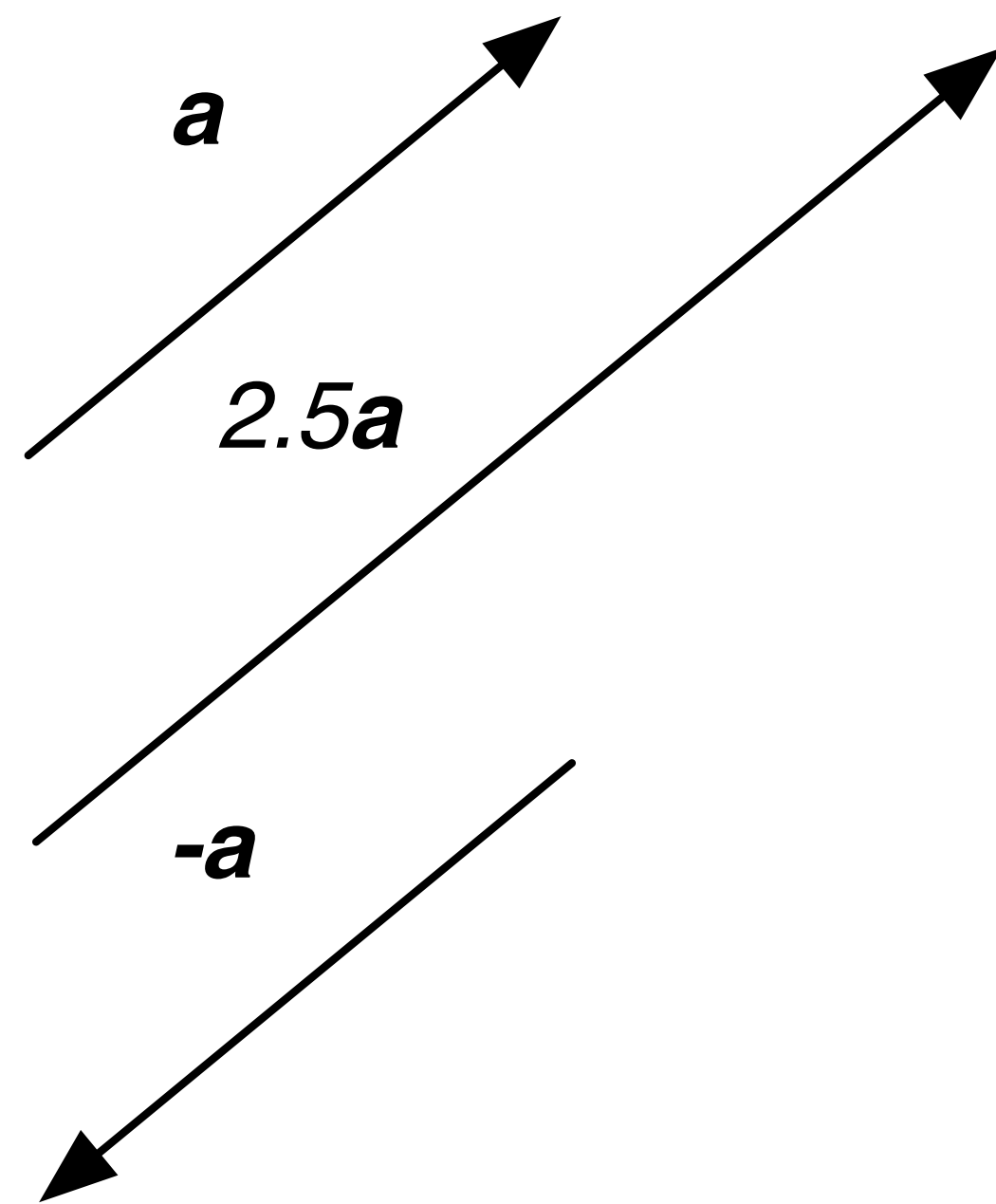
- A) shows both vectors starting at the same point, and forming two sides of a parallelogram.
- The sum of the vectors is then a diagonal of this parallelogram.
- B) shows the vector \mathbf{b} starting at the head of \mathbf{a} and draw the sum as emanating from the tail of \mathbf{a} to the head of \mathbf{b}

VectorAddition.py

```
1  #!/usr/bin/python
2  from math import *
3  from numpy import *
4
5  def inputVector() :
6      d=raw_input("enter_vector_x,y,z_>")
7      f=d.split(",")
8      Vector=array(f, dtype=float32)
9      return Vector
10
11 Vector1=inputVector()
12 Vector2=inputVector()
13
14 print Vector1 , "_+_", Vector2 , "=_" , Vector1+Vector2
```

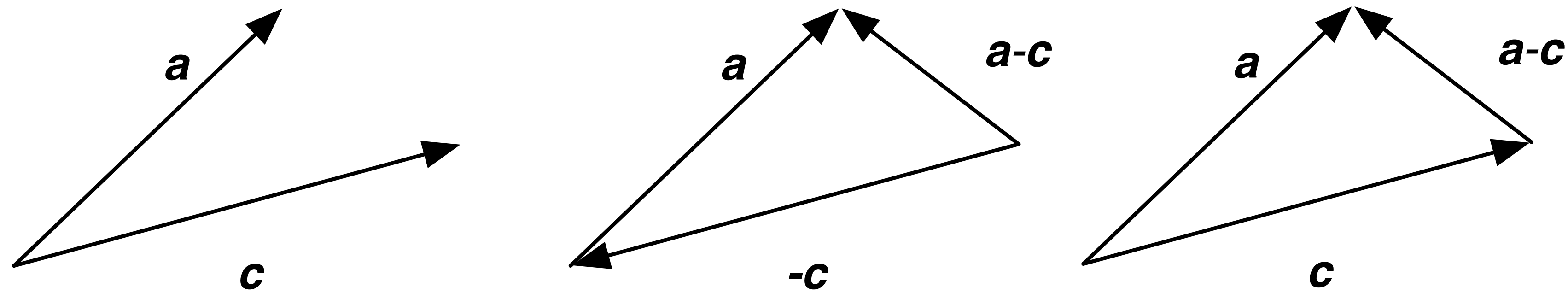
```
[jmacey@neuromancer:Lecture4]$ ./VectorAddition.py
enter vector x,y,z >2,3,4
enter vector x,y,z >3,2,1
[ 2.  3.  4.] + [ 3.  2.  1.] = [ 5.  5.  5.]
[jmacey@neuromancer:Lecture4]$ ./VectorAddition.py
enter vector x,y,z >2,3,4,5,6
enter vector x,y,z >6,5,4,2,3
[ 2.  3.  4.  5.  6.] + [ 6.  5.  4.  2.  3.] = [ 8.  8.  8.  7.  9.]
```


Vector Scaling



- The above figure shows the effect of multiplying (scaling) a vector \mathbf{a} by a scalar $s=2.5$
- This now makes the vector \mathbf{a} 2.5 times as long.
- When s is negative the direction of $s\mathbf{a}$ is opposite of \mathbf{a}
- This is shown above with $s=-1$

Vector Subtraction



- Subtraction follows easily once adding and scaling have been established
- For example $\mathbf{a-c}$ is simply $\mathbf{a+(-c)}$
- The above diagram shows this geometrically

For the vectors $\mathbf{a} = \begin{bmatrix} 1 & -1 \end{bmatrix}$ and $\mathbf{c} = \begin{bmatrix} 2 & 1 \end{bmatrix}$

The value of $\mathbf{a-c} = \begin{bmatrix} -1 & -2 \end{bmatrix}$

as

$$\mathbf{a+(-c)} = \begin{bmatrix} 1 & -1 \end{bmatrix} + \begin{bmatrix} -2 & -1 \end{bmatrix} = \begin{bmatrix} -1 & -2 \end{bmatrix}$$

VectorSubtraction.py

```
1  #!/usr/bin/python
2  from math import *
3  from numpy import *
4
5  def inputVector() :
6      d=raw_input("enter_vector_x,y,z_>")
7      f=d.split(",")
8      Vector=array(f,dtype=float32)
9      return Vector
10
11 Vector1=inputVector()
12 Vector2=inputVector()
13
14 print Vector1 , "_-_" , Vector2 , "=_" , Vector1-Vector2
15 print Vector1 , "_+_-" , Vector2 , "=_" , Vector1+(-Vector2)
```

```
[jmacey@neuromancer:Lecture4]$ ./VectorSubtraction.py
enter vector x,y,z >2,1
enter vector x,y,z >-1,1
[ 2.  1.] - [-1.  1.] = [ 3.  0.]
[ 2.  1.] + -[-1.  1.] = [ 3.  0.]
[jmacey@neuromancer:Lecture4]$ ./VectorSubtraction.py
enter vector x,y,z >3,4,5,6
enter vector x,y,z >8,2,4,3
[ 3.  4.  5.  6.] - [ 8.  2.  4.  3.] = [-5.  2.  1.  3.]
[ 3.  4.  5.  6.] + -[ 8.  2.  4.  3.] = [-5.  2.  1.  3.]
```

Linear Combinations of Vectors

- To form a linear combination of two vectors \mathbf{v} and \mathbf{w} (having the same dimensions) we scale each of them by same scalars, say a and b and add the weighted versions to form the new vector $a\mathbf{v}+b\mathbf{w}$

DEFINITION : A linear combination of the m vectors $\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_m$ is a vector of the form

$$\mathbf{w} = a_1\mathbf{v}_1 + a_2\mathbf{v}_2 + \dots + a_m\mathbf{v}_m$$

where a_1, a_2, \dots, a_m are scalars

- For example the linear combination $2[3 \ 4 \ -1] + 6[-1 \ 0 \ 2]$ forms the vector $[0 \ 8 \ 10]$
- Two special types of linear combinations, “affine” and “convex” combinations, are particularly important in graphics.

LinearCombination.py

```
1 #!/usr/bin/python
2 from math import *
3 from numpy import *
4
5 def inputVector() :
6     d=raw_input("enter_vector_x,y,z_>")
7     f=d.split(",")
8     Vector=array(f, dtype=float32)
9     return Vector
10
11 Vector1=inputVector()
12 a=float(raw_input("Enter_Scalar_a_>"))
13 Vector2=inputVector()
14 b=float(raw_input("Enter_Scalar_b_>"))
15
16 print a, "*", Vector1 , "+", b, "*", Vector2 , "=", a*Vector1+b*Vector2
```

```
[jmacey@neuromancer:Lecture4]$ ./LinearCombination.py
enter vector x,y,z >2,3,5
Enter Scalar a >2
enter vector x,y,z >3,2,5
Enter Scalar b >2.5
2.0 * [ 2.  3.  5.] + 2.5 * [ 3.  2.  5.] = [ 11.5  11.  22.5]
```

Affine Geometry

- In geometry, affine geometry is geometry not involving any notions of origin, length or angle, but with the notion of subtraction of points giving a vector.
- It occupies a place intermediate between Euclidean geometry and projective geometry.

Affine Combinations of Vectors

- A linear combination of vectors is an affine combination if the coefficients a_1, a_2, \dots, a_m add up to unity.
- Thus the linear combination in combination in the previous equation is affine if $a_1 + a_2 + \dots + a_m = 1$
- For example $3\mathbf{a}+2\mathbf{b}-4\mathbf{c}$ is an affine combination of $\mathbf{a}, \mathbf{b}, \mathbf{c}$ but $3\mathbf{a}+\mathbf{b}-4\mathbf{c}$ is not
- The combination of two vectors \mathbf{a} and \mathbf{b} are often forced to sum to unity by writing one vector as some scalar t and the other as $(1-t)$, as in

$$(1-t)\mathbf{a} + (t)\mathbf{b}$$

Convex Combinations of Vectors

- A **convex combination** arises as a further restriction on an affine combination.
- Not only must the coefficients of the linear combinations sum to unity, but each coefficient must also be non-negative, thus the linear combination of the previous equation is convex if

$$a_1 + a_2 + \dots + a_m = 1$$

and

$$a_i \geq 0, \text{ for } i = 1, \dots, m$$

Convex Combinations of Vectors

- As a consequence, all \mathbf{a}_i must lie between 0 and 1
- Accordingly $0.3\mathbf{a}+0.7\mathbf{b}$ is a convex combination but $1.8\mathbf{a}-0.8\mathbf{b}$ is not
- The set of coefficients a_1, a_2, \dots, a_m is sometimes said to form a **partition of unity**, suggesting that a unit amount of “material” is partitioned into pieces.

Magnitude of a Vector

- If a vector \mathbf{w} is represented by the n-tuple $[w_1 \quad w_2 \dots w_n]$ how may it's magnitude (equivalently, its length and size) be computed?
- We denote the magnitude by $|\mathbf{w}|$ and define it as the distance from the tail to the head of the vector.
- Using the Pythagorean theorem we obtain

$$|\mathbf{w}| = \sqrt{w_1^2 + w_2^2 + \dots + w_n^2}$$

- For example the magnitude of $\mathbf{w} = [4 \quad -2]$ is $\sqrt{4^2 + -2^2} = \sqrt{20}$
- A vector of zero length is denoted as 0
- Note that if \mathbf{w} is the vector from point A to point B , then $|\mathbf{w}|$ will be the distance from A to B

Magnitude.py

```
1 #!/usr/bin/python
2 from math import *
3 from numpy import *
4
5 def inputVector() :
6     d=raw_input("enter_vector_x,y,z...n_>")
7     f=d.split(",")
8     Vector=array(f,dtype=float32)
9     return Vector
10
11 def Magnitude(Vector) :
12     sum =0
13     for v in Vector[:]:
14         sum +=v*v
15     return sqrt(sum)
16
17 Vector=inputVector()
18
19 print "Length_of_" ,Vector, "=",linalg.norm(Vector)
20 print "Length_of_" ,Vector, "=",Magnitude(Vector)
```

```
[jmacey@neuromancer:Lecture4]$ ./Magnitude.py
enter vector x,y,z...n >1,2,3
Length of [ 1.  2.  3.] = 3.74166
Length of [ 1.  2.  3.] = 3.74165738677
[jmacey@neuromancer:Lecture4]$ ./Magnitude.py
enter vector x,y,z...n >2,5,4
Length of [ 2.  5.  4.] = 6.7082
Length of [ 2.  5.  4.] = 6.7082039325
```

Unit Vectors

- It is often useful to scale a vector so that the result has unity length.
- This type of scaling is called **normalizing** a vector, and the result is known as a **unit vector**
- For example the normalized version of a vector \mathbf{a} is denoted as $\hat{\mathbf{a}}$
- And is formed by scaling \mathbf{a} with the value $1/|\mathbf{a}|$ or $\hat{\mathbf{a}} = \frac{\mathbf{a}}{|\mathbf{a}|}$
- We will use normalized vectors for many calculations in Graphics, such as rotations, normals to a surface and some lighting calculations.

Normalize.py

```
1  #!/usr/bin/python
2  from math import *
3  from numpy import *
4
5  def inputVector() :
6      d=raw_input("enter_vector_x,y,z...n_>")
7      f=d.split(",")
8      Vector=array(f,dtype=float32)
9      return Vector
10
11 def Magnitude(Vector) :
12     sum =0
13     for v in Vector[:] :
14         sum +=v*v
15     return sqrt(sum)
16
17 def Normalize(Vector) :
18     return Vector / Magnitude(Vector)
19
20 Vector=inputVector()
21
22 print "Normalized_version_of_" ,Vector, "=",Vector/linalg.norm(Vector)
23 print "Normalized_version_of_" ,Vector, "=",Normalize(Vector)
```

```
[jmacey@neuromancer:Lecture4]$ ./Normalized.py
enter vector x,y,z...n >2,4,5
Normalized version of [ 2.  4.  5.] = [ 0.2981424  0.59628481  0.74535602]
Normalized version of [ 2.  4.  5.] = [ 0.2981424  0.59628481  0.74535602]
```

The Dot Product

- The dot product of two vectors is simple to define and compute
- For a two dimensional vector $\begin{bmatrix} a_1 & a_2 \end{bmatrix}$ and $\begin{bmatrix} b_1 & b_2 \end{bmatrix}$, it is simply the scalar whose value is $a_1b_1 + a_2b_2$
- Thus to calculate the dot product we multiply the corresponding components of the two vectors and add the the results
- For example for two vectors $\begin{bmatrix} 3 & 4 \end{bmatrix}$ and $\begin{bmatrix} 1 & 6 \end{bmatrix}$ the dot product = 27
- And $\begin{bmatrix} 2 & 3 \end{bmatrix}$ and $\begin{bmatrix} 9 & -6 \end{bmatrix} = 0$
- The generalized version of the dot product is shown below

The dot product d of two n dimensional vectors $\mathbf{v} = \begin{bmatrix} v_1 & v_2 \dots & v_n \end{bmatrix}$ and $\mathbf{w} = \begin{bmatrix} w_1 & w_2 \dots & w_n \end{bmatrix}$ is denoted as $\mathbf{v} \bullet \mathbf{w}$ and has the value

$$d = \mathbf{v} \bullet \mathbf{w} = \sum_{i=1}^n v_i w_i$$

Properties of the Dot Product

- The dot product exhibits four major properties as follows
 1. **Symmetry:** $\mathbf{a} \bullet \mathbf{b} = \mathbf{b} \bullet \mathbf{a}$
 2. **Linearity:** $(\mathbf{a} + \mathbf{c}) \bullet \mathbf{b} = \mathbf{a} \bullet \mathbf{b} + \mathbf{c} \bullet \mathbf{b}$
 3. **Homogeneity:** $(s\mathbf{a}) \bullet \mathbf{b} = s(\mathbf{a} \bullet \mathbf{b})$
 4. $|\mathbf{b}|^2 = \mathbf{b} \bullet \mathbf{b}$
- The dot product is **commutative** that means the order in which the vectors are combined does not matter.
- The final expression asserts that taking the dot product of a vector with itself yields the **square of the length** of the vector. This is usually expressed in the following form $|\mathbf{b}| = \sqrt{\mathbf{b} \bullet \mathbf{b}}$

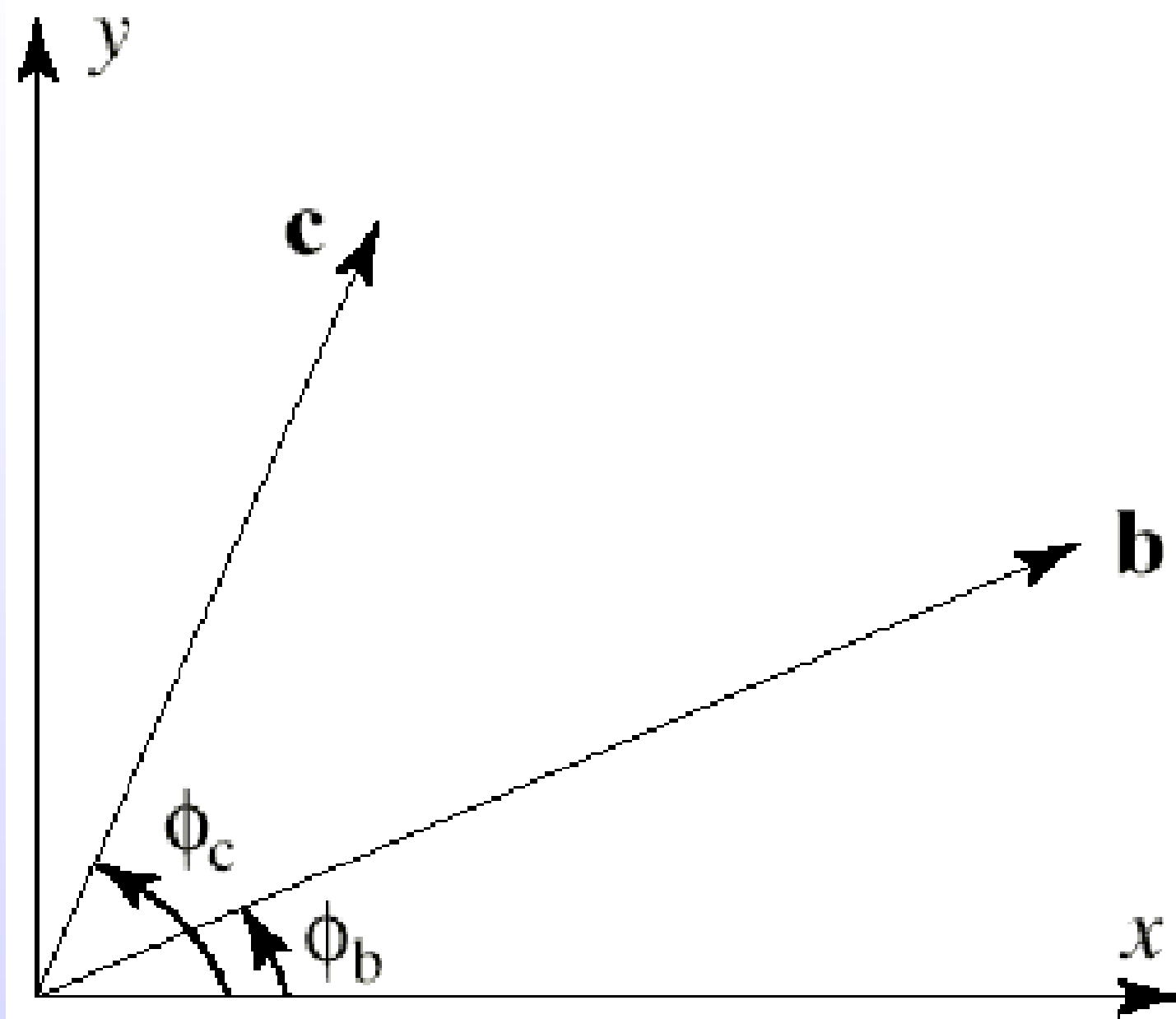
DotProduct.py

```
1 #!/usr/bin/python
2 from math import *
3 from numpy import *
4
5 def inputVector() :
6     d=raw_input("enter_vector_x,y,z...n_>")
7     f=d.split(",")
8     Vector=array(f, dtype=float32)
9     return Vector
10
11 def Magnitude(Vector) :
12     sum =0
13     for v in Vector[:]:
14         sum +=v*v
15     return sqrt(sum)
16
17
18 Vector1=inputVector()
19 Vector2=inputVector()
20 Vector3=inputVector()
21 s=float(raw_input("Enter_a_Scalar_>"))
22
23 print "Symmetry"
24 print Vector1, ". ", Vector2, "=", dot(Vector1, Vector2)
25 print Vector2, ". ", Vector1, "=", dot(Vector2, Vector1)
26 print "Linearity_"
27 print "(", Vector1, "+", Vector3, ") . ", Vector2, "=", dot((Vector1+Vector3), Vector2)
28 print "(", Vector1, ". ", Vector3, ") + (", Vector2, ". ", Vector3, ") =", dot(Vector1, Vector2) + dot(Vector3
    , Vector2)
29 print "Homogeneity"
30 print "(", s, "*", Vector1, ") . ", Vector2, "_=_", dot(s*Vector1, Vector2)
31 print s, "*"(" ", Vector1, ". ", Vector2, ") =_", s*dot(Vector1, Vector2)
32 print "Magnitude_Squared"
33 mag=Magnitude(Vector1)
34 print "Magnitude(", Vector1, ") =", mag*mag, "=", Vector1, ". ", Vector2, "=", dot(Vector1, Vector1)
```

```
[jmacey@neuromancer:Lecture4]$ ./DotProduct.py
enter vector x,y,z...n >2,3,4
enter vector x,y,z...n >3,2,1
enter vector x,y,z...n >6,5,2
Enter a Scalar >2
Symmetry
[ 2.  3.  4.] . [ 3.  2.  1.] = 16.0
[ 3.  2.  1.] . [ 2.  3.  4.] = 16.0
Linearity
([ 2.  3.  4.] + [ 6.  5.  2.]) . [ 3.  2.  1.] = 46.0
([ 2.  3.  4.] . [ 6.  5.  2.]) + ([ 3.  2.  1.] . [ 6.  5.  2.]) = 46.0
Homogeneity
(2.0 * [ 2.  3.  4.]) . [ 3.  2.  1.] = 32.0
2.0 * ([ 2.  3.  4.] . [ 3.  2.  1.]) = 32.0
Magnitude Squared
Magnitude([ 2.  3.  4.]) = 29.0 = [ 2.  3.  4.] . [ 3.  2.  1.] = 29.0
```


The angle between two vectors

- The most important application of the dot product is in finding the angle between two vectors or between intersecting lines.
- The figure shows the vectors \mathbf{b} and \mathbf{c} which lie at angles ϕ_b and ϕ_c relative to the x axis.



From basic trigonometry we get $\mathbf{b} = (|\mathbf{b}| \cos\phi_b, |\mathbf{b}| \sin\phi_b)$ and $\mathbf{c} = (|\mathbf{c}| \cos\phi_c, |\mathbf{c}| \sin\phi_c)$

Thus the dot product of \mathbf{b} and \mathbf{c} is

$$\mathbf{b} \bullet \mathbf{c} = |\mathbf{b}| |\mathbf{c}| \cos\phi_c \cos\phi_b + |\mathbf{b}| |\mathbf{c}| \sin\phi_b \sin\phi_c = |\mathbf{b}| |\mathbf{c}| \cos(\phi_c - \phi_b),$$

so for any two vectors \mathbf{b} and \mathbf{c} ,

$$\mathbf{b} \bullet \mathbf{c} = |\mathbf{b}| |\mathbf{c}| \cos(\theta),$$

where θ is the angle from \mathbf{b} to \mathbf{c} .

Hence, $\mathbf{b} \bullet \mathbf{c}$ varies as the cosine of the angle from \mathbf{b} to \mathbf{c} .

Normalised Vector angles

- To obtain a more compact form the normalized vectors are usually used
- Therefore both sides are divided by $|\mathbf{b}| |\mathbf{c}|$ and the unit vector notation is used so $\hat{\mathbf{b}} = \frac{\mathbf{b}}{|\mathbf{b}|}$ to obtain $\cos(\theta) = \hat{\mathbf{b}} \cdot \hat{\mathbf{c}}$
- So the cosine of the angle between two vectors \mathbf{b} and \mathbf{c} is the dot product of the normalized vectors.

Example

find the angle between two vectors $\mathbf{b} = \begin{bmatrix} 3 & 4 \end{bmatrix}$ and $\mathbf{c} = \begin{bmatrix} 5 & 2 \end{bmatrix}$

$$|\mathbf{b}| = \sqrt{3^2 + 4^2} = 5 \text{ and } |\mathbf{c}| = \sqrt{5^2 + 2^2} = 5.3851$$

$$\text{so that } \hat{\mathbf{b}} = \begin{bmatrix} \frac{3}{5} & \frac{4}{5} \end{bmatrix} \text{ and } \hat{\mathbf{c}} = \begin{bmatrix} \frac{5}{5.3851} & \frac{2}{5.3851} \end{bmatrix}$$

$$\text{This gives us } \hat{\mathbf{b}} = \begin{bmatrix} 0.6 & 0.8 \end{bmatrix} \text{ and } \hat{\mathbf{c}} = \begin{bmatrix} 0.9285 & 0.3714 \end{bmatrix}$$

$$\text{The dot product } \hat{\mathbf{b}} \bullet \hat{\mathbf{c}} = 0.5571 + 0.296 = 0.8542 = \cos(\theta)$$

hence $\theta = 31.326^\circ$ from the inverse cosine

this can then be expanded to work for 3 or 4 dimensions

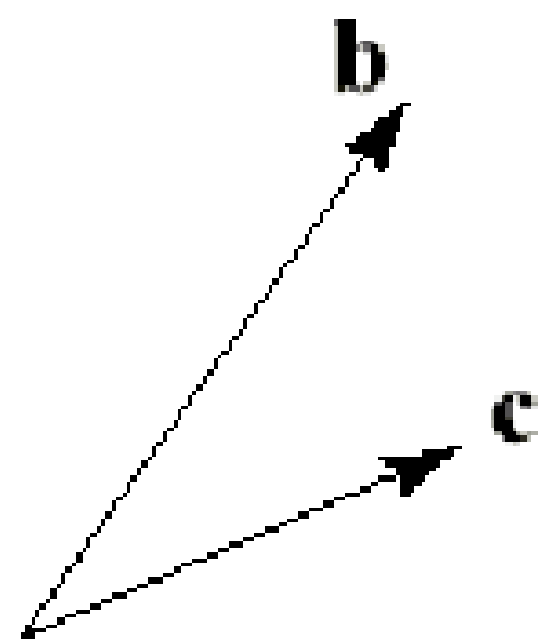
AngleBetween.py

```
1  #!/usr/bin/python
2  from math import *
3  from numpy import *
4
5  def inputVector() :
6      d=raw_input("enter_vector_x,y,z...n_>")
7      f=d.split(",")
8      Vector=array(f, dtype=float32)
9      return Vector
10
11 def Magnitude(Vector) :
12     sum =0
13     for v in Vector[:]:
14         sum +=v*v
15     return sqrt(sum)
16
17 def Normalize(Vector) :
18     return Vector / Magnitude(Vector)
19
20 Vector1=inputVector()
21 Vector2=inputVector()
22
23 Vector1=Normalize(Vector1)
24 Vector2=Normalize(Vector2)
25 ndot=dot(Vector1, Vector2)
26 print "Normalized_vectors_", Vector1, Vector2
27 angle = acos(ndot)
28 print "Angle_between_=", degrees(angle)
```

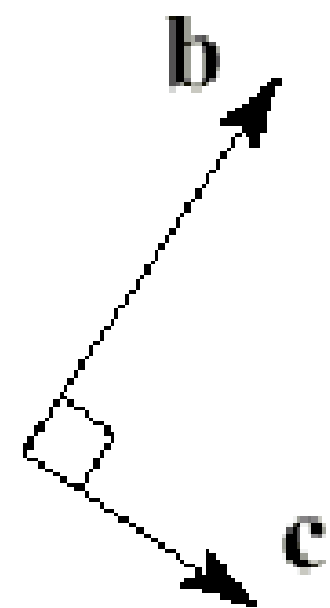
```
[jmacey@neuromancer:Lecture4]$ ./AngleBetween.py
enter vector x,y,z...n >3,4
enter vector x,y,z...n >5,2
Normalized vectors [ 0.60000002  0.80000001] [ 0.92847669  0.37139067]
Angle between = 31.3286907294
[jmacey@neuromancer:Lecture4]$ ./AngleBetween.py
enter vector x,y,z...n >0,1,0
enter vector x,y,z...n >0,0,1
Normalized vectors [ 0.  1.  0.] [ 0.  0.  1.]
Angle between = 90.0
[jmacey@neuromancer:Lecture4]$ ./AngleBetween.py
enter vector x,y,z...n >0,1,0
enter vector x,y,z...n >0.5,0.5,0
Normalized vectors [ 0.  1.  0.] [ 0.70710677  0.70710677  0. ]
Angle between = 45.0000009806
```

The sign of $\mathbf{b} \bullet \mathbf{c}$ and perpendicularity

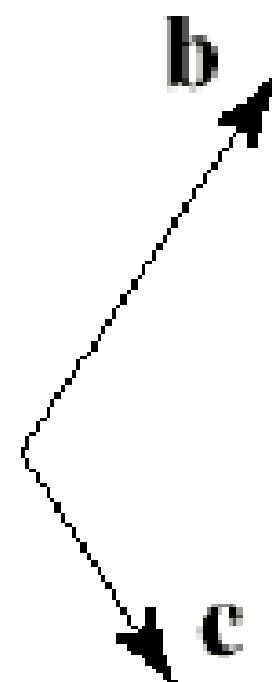
- $\cos(\theta)$ is **positive** if $|\theta|$ is less than 90° , **zero** if $|\theta|$ equals 90° , and **negative** if $|\theta|$ exceeds 90° .
- Because the dot product of two vectors is proportional to the cosine of the angle between them, we can observe immediately that two vectors (of any non zero length) are



$$\mathbf{b} \bullet \mathbf{c} > 0$$



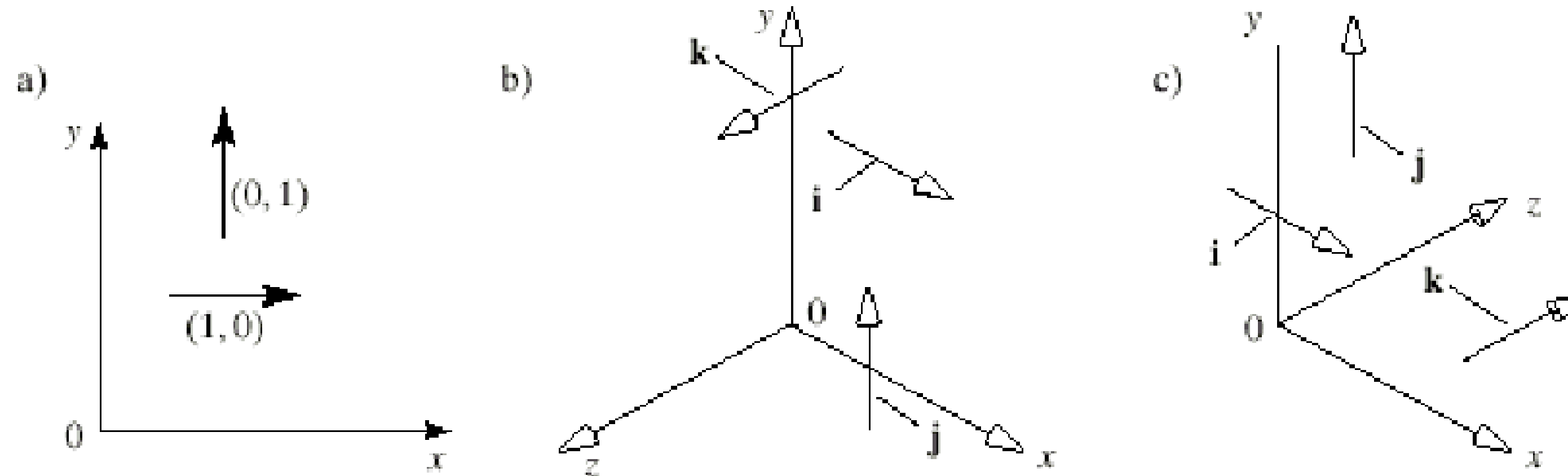
$$\mathbf{b} \bullet \mathbf{c} = 0$$



$$\mathbf{b} \bullet \mathbf{c} < 0$$

less than	90° apart	if $\mathbf{b} \bullet \mathbf{c} > 0$;
exactly	90° apart	if $\mathbf{b} \bullet \mathbf{c} = 0$;
more than	90° apart	if $\mathbf{b} \bullet \mathbf{c} < 0$;

The standard unit Vector

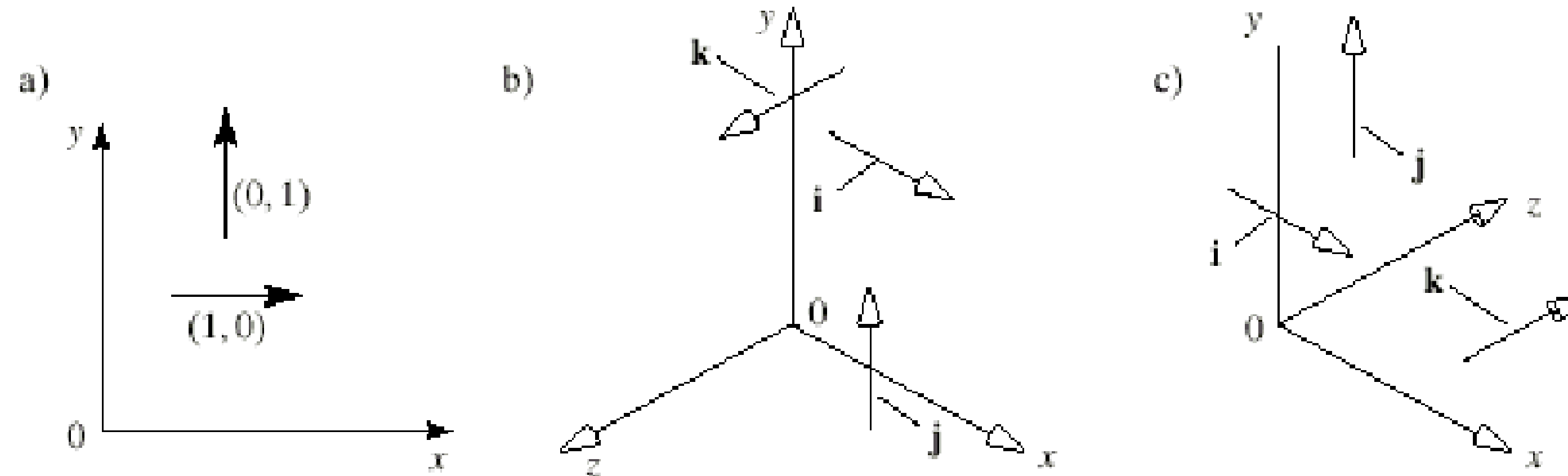


- The case in which the vectors are 90° apart, or **perpendicular** is of special importance

Definition : Vectors **b** and **c** are perpendicular if $\mathbf{b} \bullet \mathbf{c} = 0$

- Other names for “perpendicular” are **orthogonal** and **normal** and they are used interchangeably.
- The most familiar examples of orthogonal vectors are those aimed along the axes of 2D and 3D coordinate systems as shown

The standard unit Vector



- The vectors \mathbf{i} , \mathbf{j} and \mathbf{k} are called standard unit vectors and are defined as follows

$$\mathbf{i} = \begin{bmatrix} 1 & 0 & 0 \end{bmatrix} \quad \mathbf{j} = \begin{bmatrix} 0 & 1 & 0 \end{bmatrix} \quad \text{and} \quad \mathbf{k} = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}$$

Cartesian Vectors

- Let us define three Cartesian unit vectors i , j , k that are aligned with the x , y , z axes:

$$i = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} \quad j = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} \quad k = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$$

- Any vector aligned with the x -, y - or z -axes can be defined by a scalar multiple of the unit vectors i , j , k .
- A vector 10 units long aligned with the x -axis is $10i$.
- A vector 20 units long aligned with the z -axis is $20k$.
- By employing the rules of vector addition and subtraction, we can define a vector \mathbf{r} by adding three Cartesian vectors as follows:

$$\mathbf{r} = a\mathbf{i} + b\mathbf{j} + c\mathbf{k}$$

Cartesian Vectors

$$\mathbf{r} = a\mathbf{i} + b\mathbf{j} + c\mathbf{k}$$

- This is equivalent to writing

$$\mathbf{r} = \begin{bmatrix} a \\ b \\ c \end{bmatrix}$$

Therefore the magnitude of \mathbf{r} is $|\mathbf{r}| = \sqrt{a^2 + b^2 + c^2}$

- A pair of Cartesian vectors such \mathbf{r} and \mathbf{s} can be combined as follows

$$\mathbf{r} = a\mathbf{i} + b\mathbf{j} + c\mathbf{k}$$

$$\mathbf{s} = d\mathbf{i} + e\mathbf{j} + f\mathbf{k}$$

$$\mathbf{r} \pm \mathbf{s} = [a \pm d]\mathbf{i} + [b \pm e]\mathbf{j} + [c \pm f]\mathbf{k}$$

Cartesian Vectors Example

$$\mathbf{r} = 2\mathbf{i} + 3\mathbf{j} + 4\mathbf{k} \text{ and } \mathbf{s} = 5\mathbf{i} + 6\mathbf{j} + 7\mathbf{k}$$

$$\mathbf{r} + \mathbf{s} = 7\mathbf{i} + 9\mathbf{j} + 11\mathbf{k}$$

$$|\mathbf{r} + \mathbf{s}| = \sqrt{7^2 + 9^2 + 11^2} = \sqrt{251} = 15.84$$

The cross product of two vectors

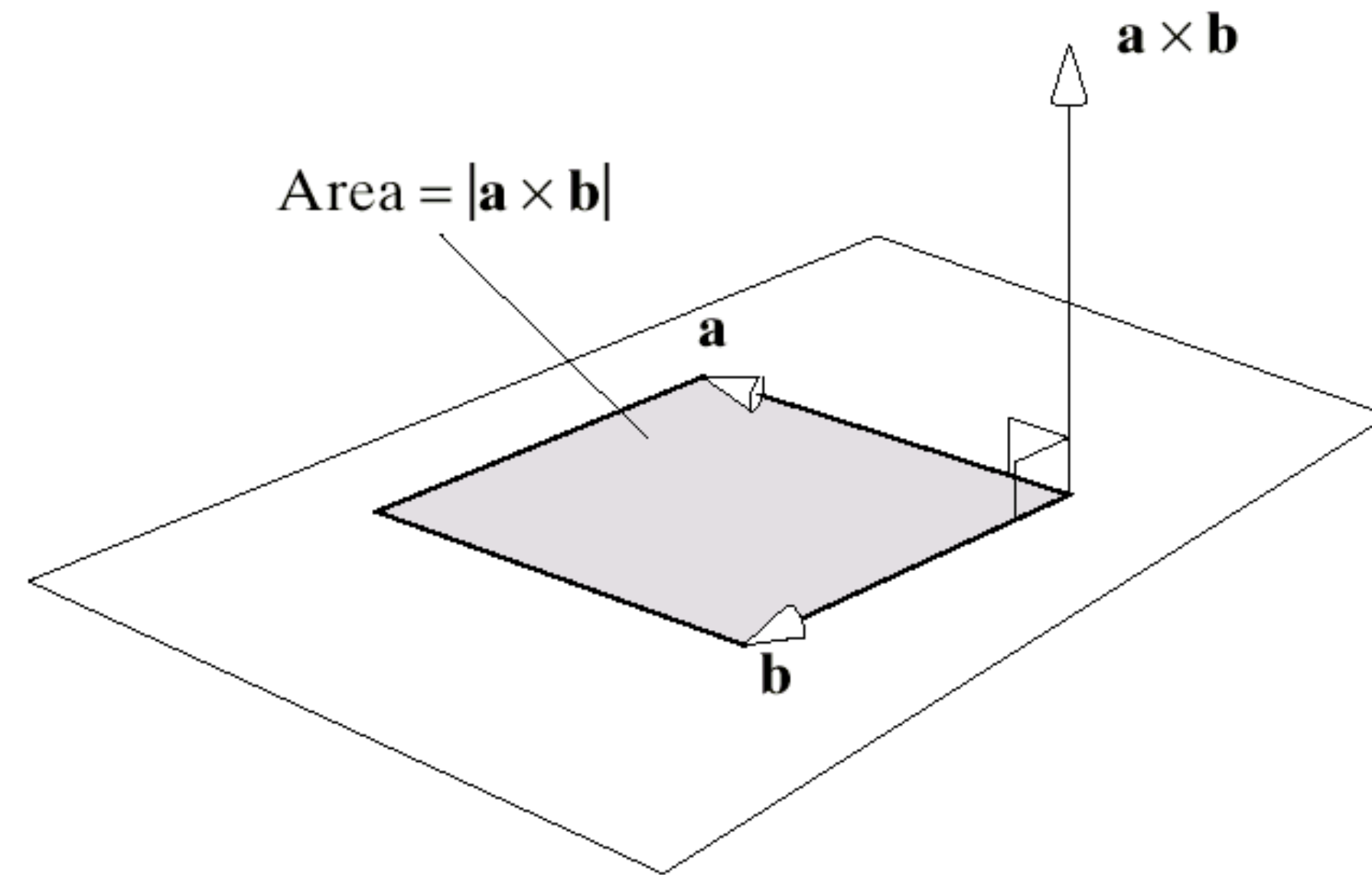
- The **cross product** (also called the **vector product**) of two vectors is another vector.
- It has many useful properties but the most useful is the fact that it is perpendicular to both of the given vectors
- Given the 3D vectors $\mathbf{a} = [a_x \ a_y \ a_z]$ and $\mathbf{b} = [b_x \ b_y \ b_z]$ their cross product is denoted as $\mathbf{a} \times \mathbf{b}$
- It is defined in terms of the standard unit vectors \mathbf{i} , \mathbf{j} and \mathbf{k} as

$$\mathbf{a} \times \mathbf{b} = [a_y b_z - a_z b_y]\mathbf{i} + [a_z b_x - a_x b_z]\mathbf{j} + [a_x b_y - a_y b_x]\mathbf{k}$$

This form is usually replaced using the determinant as follows

$$\mathbf{a} \times \mathbf{b} = \begin{vmatrix} \mathbf{i} & \mathbf{j} & \mathbf{k} \\ a_x & a_y & a_z \\ b_x & b_y & b_z \end{vmatrix}$$

Geometric interpretation of the Cross Product



- By definition the cross product $\mathbf{a} \times \mathbf{b}$ of two vectors is another vector and has the following properties
- $\mathbf{a} \times \mathbf{b}$ is perpendicular (orthogonal) to both \mathbf{a} and \mathbf{b}
- The length of $\mathbf{a} \times \mathbf{b}$ equals the area of the parallelogram determined by \mathbf{a} and \mathbf{b} this area is equal to $|\mathbf{a} \times \mathbf{b}| = |\mathbf{a}| |\mathbf{b}| \sin(\theta)$ where θ is the angle between \mathbf{a} and \mathbf{b} measured from \mathbf{a} to \mathbf{b} or \mathbf{b} to \mathbf{a} , whichever produces an angle less than 180°

CrossProduct.py

```
1 #!/usr/bin/python
2 from math import *
3 from numpy import *
4
5 def inputVector() :
6     d=raw_input("enter_vector_x,y,z...n_>")
7     f=d.split(",")
8     Vector=array(f,dtype=float32)
9     return Vector
10
11 def Magnitude(Vector) :
12     sum =0
13     for v in Vector[:]:
14         sum +=v*v
15     return sqrt(sum)
16
17 Vector1=inputVector()
18 Vector2=inputVector()
19
20 print Vector1,"x",Vector2,"_=_",cross(Vector1,Vector2)
21 print "Area_of_Vectors_=_",Magnitude(cross(Vector1,Vector2))
```

```
[jmacey@neuromancer:Lecture4]$ ./CrossProduct.py
enter vector x,y,z...n >0,0,1 (Vector) :
enter vector x,y,z...n >1,0,0
[ 0.  0.  1.] x [ 1.  0.  0.] = [ 0.  1.  0.]
[jmacey@neuromancer:Lecture4]$ ./CrossProduct.py
enter vector x,y,z...n >0,1,0 (sum)
enter vector x,y,z...n >1,0,0
[ 0.  1.  0.] x [ 1.  0.  0.] = [ 0.  0. -1.]
Area of Vectors = 1.0
[jmacey@neuromancer:Lecture4]$ ./CrossProduct.py
enter vector x,y,z...n >2,3,4
enter vector x,y,z...n >4,3,2
[ 2.  3.  4.] x [ 4.  3.  2.] = [ -6.  12. -6.]
Area of Vectors = 14.6969384567
```

References

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