$\mathbf{x} = egin{bmatrix} x_1 \ x_2 \ dots \ x_m \end{bmatrix}$

In physics, vector has a direction and magnitude, like velocity of a moving object.

In data analysis, a series of discrete data can be expressed as a vector (let's say there are m data points, then you have a m-dimensional vector)

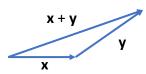
In computational model, model state can be expressed as a vector (e.g. chemical concentrations in box models, dynamic height in geophys fluid dynamics, with m being the number of grid points)

1

Vector

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix} \quad \mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}$$

When there are more then two vectors, they can add together to form another vector

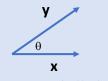


Vectors can multiply together: inner product produces a scalar (remember "row times column")

$$\mathbf{x} \cdot \mathbf{y} = \mathbf{x}^T \mathbf{y} = \begin{bmatrix} x_1 x_2 \cdots x_m \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}$$

$$= x_1y_1 + x_2y_2 + \cdots + x_my_m$$

In a 2D example,



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

3

Vector

Vectors can multiply together: inner product produces a scalar (remember "row times column")

The projection of **x** onto **y** is:

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

In a 2D example,



^

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

Vectors can multiply together: inner product produces a scalar (remember "row times column")

The projection of **y** onto **x** is:

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

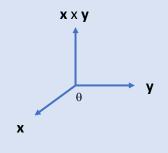
In a 2D example, $\mathbf{x} \cdot \mathbf{y} = |\mathbf{x}| |\mathbf{y}| cos\theta$

5

Vector

Vectors can multiply in a different way: cross product produces a vector (remember "the right hand rule")

$$\mathbf{x} \times \mathbf{y} = |\mathbf{x}| |\mathbf{y}| sin\theta \mathbf{\hat{z}}$$



Vectors can multiply together in another different ways: **outer product produces** a matrix (again, remember "row times column")

$$\mathbf{x}\mathbf{y}^T = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix} \begin{bmatrix} y_1 y_2 \cdots y_m \end{bmatrix} = \begin{bmatrix} x_1 y_1 x_1 y_2 \cdots x_1 y_m \\ x_2 y_1 x_2 y_2 \cdots x_2 y_m \\ \vdots \\ x_m y_1 x_m y_2 \cdots x_m y_m \end{bmatrix}$$

7

Inner product and (co)variance

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_m \end{bmatrix}$$

In data analysis, vector can contain a collection of measurements (e.g. mean August temperature of Atlanta from last 140 years)

Inner product and (co)variance

$$\mathbf{x}' = egin{bmatrix} x_1 - \overline{x} \ x_2 - \overline{x} \ dots \ x_m - \overline{x} \end{bmatrix} = egin{bmatrix} x_1' \ x_2' \ dots \ x_m' \end{bmatrix}$$

Let's subtract mean of **x** from all elements, so **x** becomes **x'**

9

Inner product and (co)variance

$$\mathbf{x}' \cdot \mathbf{x}' = |\mathbf{x}'|^2 = \Sigma x_n'^2 = (N-1)\sigma^2 = (N-1)\sigma_{xx}$$

Inner product of x' with itself the square of the "length" of the x' vector.

It is equal to the variance (σ^2 or σ_{xx}) of the data contained in vector x multiplied by N-1

The "length" |x'| is also called the L2 norm

Inner product and (co)variance

$$\mathbf{x}' \cdot \mathbf{y}' = \Sigma x_n' y_n' = (N-1)\sigma_{xy}$$

Inner product of x' and y' is:

- (1) the **covariance** of the data contained in vector **x** and **y** (multiplied by N-1)
- (2) the **projection** of x onto y (multiplied by |y'|)
- (3) Proportional to the correlation between x and y

11

Inner product and (co)variance

$$\mathbf{x}' \cdot \mathbf{y}' = \Sigma x_n' y_n' = (N-1)\sigma_{xy}$$

Inner product of x' and y' is:

- (1) the covariance of the data contained in vector **x** and **y** (multiplied by N-1)
- (2) the **projection** of x onto y (multiplied by |y'|)

Matrix-vector product and $\mathbf{A}\mathbf{x} = \mathbf{b}$

A (2 x 2) example

$$\begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 0 \\ 2 \end{bmatrix}$$

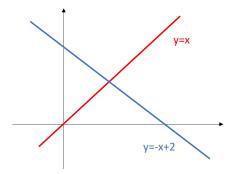
 $A \qquad x = k$

The "row" point of view:

$$x - y = 0$$

Intersection of two lines

$$x + y = 2$$



The problem **Ax** = **b** is solvable only if **the two lines intersect at a point**

13

Matrix-vector product and $\mathbf{A}\mathbf{x} = \mathbf{b}$

Inverse matrix $\mathbf{A}^{ ext{-}1}$ $\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}$

If inverse matrix of **A** exists, we have

In MATLAB it is **inv** function. Also the backslash operation "A\b" does it for you...

In Python, np.linalg.inv (or scipy.linalg.inv)

```
% create a random matrix A and a vector b
A=rand(2,2);
b=rand(2,1);
% solve A^-1 b
x=inv(A)*b
```

 $x = 2 \times 1$ -1.1415 1.9246

x=A\b

 $x = 2 \times 1$ -1.1415 1.9246

Matrix-vector product and $\mathbf{A}\mathbf{x} = \mathbf{b}$

What if **A** is not a square matrix?

Let's say there are too many (m) equations than (n) unknowns.

In this case, there is no unique solution \mathbf{x} that can satisfy all equations in $\mathbf{A}\mathbf{x} = \mathbf{b}$ in the exact sense

15

Matrix-vector product and $\mathbf{A}\mathbf{x} = \mathbf{b}$

Consider **A** is $(m \times 2)$ matrix, **x** is (2×1) and **b** is $(m \times 1)$ and m is much larger than 2.

In this case, **A x** is unlikely equal to **b** in the exact sense.

However, we could look for the approximate solution \mathbf{x} that minimizes the magnitude of the misfit $|\mathbf{A}\mathbf{x} - \mathbf{b}|$ (aka least square method).

Matrix-vector product and $\mathbf{A}\mathbf{x} = \mathbf{b}$

In MATLAB, "backslash"(\) takes care of this problem.

It is also called pseudoinverse problem, and "pinv" is the MATLAB function.

In python, it is available as numpy.linalg.pinv or scipy.linalg.pinv

```
A=rand(20,2);
b=rand(20,1);
% solve A^-1 b
x=A\b
x = 2×1
0.2472
0.8127
```

x=pinv(A)*b

x = 2×1 0.2472 0.8127

x=inv(A)*b

Error using <u>inv</u> Matrix must be square.