
Lecture 1: Data, Vectorization, Affine Functions, and a Single Neuron

Main goal. Understand how data can be represented as vectors, how a learning task can be formulated as a function between vector spaces, and how affine functions and neurons arise naturally.

1. Why Linear Algebra?

Modern AI relies on three major ingredients:

computing power + machine learning + massive data

The goal of this course is to understand some of the mathematical tools underlying these ideas.

A central mathematical language: Linear Algebra

Chapter 1 provides motivation. The main mathematical development begins in Chapter 2.

2. Data as Vectors

For a positive integer N , define

$$[N] := \{0, 1, \dots, N-1\}.$$

A vector in $\mathbb{R}^N$ is written as

$$\mathbf{x} = \begin{pmatrix} x_0 \\ x_1 \\ \vdots \\ x_{N-1} \end{pmatrix} \in \mathbb{R}^N.$$

A large amount of digital data can be represented as vectors.

Example: RGB image.

Suppose an image has 1000×1000 pixels. Each pixel has three color values:

$$\begin{pmatrix} r \\ g \\ b \end{pmatrix} \in [0, 1]^3.$$

Hence the image contains

$$3(1000)(1000) = 3 \times 10^6$$

real numbers.

After vectorization,

$$x_{\text{image}} \in \mathbb{R}^{3 \times 10^6}.$$

Thus,

$$\text{image} \longrightarrow \text{very large vector.}$$

3. A Learning Problem as a Function

Example: cat vs. dog classification.

Let

$$x_{\text{cat}}, x_{\text{dog}} \in \mathbb{R}^{3 \times 10^6}.$$

Assign labels

$$0 = \text{cat}, \quad 1 = \text{dog}.$$

The classification problem becomes the problem of finding

$$f : \mathbb{R}^{3 \times 10^6} \longrightarrow \{0, 1\}$$

such that

$$f(x_{\text{cat}}) = 0, \quad f(x_{\text{dog}}) = 1.$$

Another example: image denoising.

Now the output is another image:

$$f : \mathbb{R}^{3 \times 10^6} \longrightarrow \mathbb{R}^{3 \times 10^6}.$$

We want

$$f(x_{\text{noisy}}) \approx x_{\text{clean}}.$$

Thus, many computational problems have the form

$$\text{data} = \text{vectors}, \quad \text{task} = \text{function.}$$

Question:

What kinds of functions can we conveniently build on a computer?

4. Inner Products and Affine Functions

For $x, w \in \mathbb{R}^N$, define the inner product

$$\langle x, w \rangle = \sum_{j=0}^{N-1} x_j w_j.$$

Definition (Affine function). *Fix*

$$w \in \mathbb{R}^N, \quad b \in \mathbb{R}.$$

Define

$$a_{w,b} : \mathbb{R}^N \rightarrow \mathbb{R}$$

by

$$\boxed{a_{w,b}(x) = \langle x, w \rangle + b.}$$

Here w is the weight vector and b is the bias.

Example.

Let

$$x = \begin{pmatrix} x_0 \\ x_1 \end{pmatrix}, \quad w = \begin{pmatrix} 2 \\ -1 \end{pmatrix}, \quad b = 3.$$

Then

$$a_{w,b}(x) = 2x_0 - x_1 + 3.$$

An affine function can also be written using one higher-dimensional inner product:

$$\boxed{\langle x, w \rangle + b = \left\langle \begin{pmatrix} x \\ 1 \end{pmatrix}, \begin{pmatrix} w \\ b \end{pmatrix} \right\rangle.}$$

5. A Single Neuron

Let

$$\sigma : \mathbb{R} \rightarrow \mathbb{R}$$

be a nonlinear function.

Definition (Neuron). *A neuron is a function*

$$\eta : \mathbb{R}^N \rightarrow \mathbb{R}$$

of the form

$$\boxed{\eta(x) = \sigma(\langle x, w \rangle + b).}$$

Thus

$$\boxed{x \longrightarrow \langle x, w \rangle + b \longrightarrow \sigma(\langle x, w \rangle + b).}$$

Some common activation functions are:

$$\text{Step function:} \quad \sigma(t) = \begin{cases} 0, & t \leq 0, \\ 1, & t > 0, \end{cases}$$

$$\text{Sigmoid:} \quad \sigma(t) = \frac{1}{1 + e^{-t}},$$

Hyperbolic tangent: $\sigma(t) = \tanh(t)$,

and

$$\boxed{\text{ReLU}(t) = \max\{0, t\}.$$