

Lecture 4-5: Why Do We Need More Linear Algebra? Network Compression as a Motivating Problem. Span, Inner product, and Norms.

Previously, we saw that a FNN of the form

$$x \mapsto \sigma(Wx + b).$$

In practice, W is huge.

One simple idea: compress a matrix

Suppose

$$W \approx UV,$$

where

$$U \in \mathbb{R}^{m \times r}, \quad V \in \mathbb{R}^{r \times n}, \quad r \ll \min(m, n).$$

Then

$$Wx \approx U(Vx).$$

Instead of storing mn numbers, we store

$$mr + rn = r(m + n).$$

But now the obvious question is:

$\text{How do we know whether } UV \text{ is close to } W?$

Or more generally,

$\min_{\text{rank}(B) \leq r} \|W - B\|.$

Let

$$A \in \mathbb{R}^{m \times n}, \quad x \in \mathbb{R}^n.$$

Then

$$Ax = x_1 a_1 + \cdots + x_n a_n.$$

Ax is a linear combination of the columns of A .

Therefore,

$$\text{Range}(A) = \{Ax : x \in \mathbb{R}^n\} = \text{span}\{a_1, \dots, a_n\}.$$

So

$$\boxed{\text{Range}(A) = \text{ColumnSpace}(A).}$$

This will become important when we discuss rank and low-dimensional representations.

Inner Products

For

$$x, y \in \mathbb{R}^n,$$

define

$$\boxed{\langle x, y \rangle = x^T y = \sum_{j=0}^{n-1} x_j y_j.}$$

Recall the basic properties:

$$\begin{aligned}\langle x, y \rangle &= \langle y, x \rangle, \\ \langle \alpha x + \beta y, z \rangle &= \alpha \langle x, z \rangle + \beta \langle y, z \rangle.\end{aligned}$$

$$\langle x, x \rangle = \sum_j x_j^2 \geq 0,$$

with equality only when $x = 0$.

Geometric property: for nonzero x, y ,

$$\cos \theta = \frac{\langle x, y \rangle}{\sqrt{\langle x, x \rangle} \sqrt{\langle y, y \rangle}}.$$

or

$$\boxed{\cos \theta = \frac{\langle x, y \rangle}{\|x\|_2 \|y\|_2}.$$

To prove this, normalize the two vectors:

$$u = \frac{x}{\|x\|_2}, \quad v = \frac{y}{\|y\|_2}.$$

Then

$$\|u\|_2 = \|v\|_2 = 1,$$

and the angle between u and v is still θ .

Although u and v may lie in a high-dimensional space $\mathbb{R}^n$, they both belong to the at-most two-dimensional subspace

$$\text{span}\{u, v\}.$$

Therefore, ordinary two-dimensional geometry applies.

Consider the triangle whose sides are u , v , and $u - v$. By the law of cosines,

$$\|u - v\|_2^2 = \|u\|_2^2 + \|v\|_2^2 - 2\|u\|_2\|v\|_2 \cos \theta.$$

Since $\|u\|_2 = \|v\|_2 = 1$,

$$\|u - v\|_2^2 = 2 - 2 \cos \theta. \quad (1)$$

On the other hand, using the inner product,

$$\begin{aligned} \|u - v\|_2^2 &= \langle u - v, u - v \rangle \\ &= \langle u, u \rangle - 2\langle u, v \rangle + \langle v, v \rangle \\ &= 2 - 2\langle u, v \rangle. \end{aligned} \quad (2)$$

Comparing (1) and (2), we obtain

$$2 - 2 \cos \theta = 2 - 2\langle u, v \rangle,$$

so

$$\cos \theta = \langle u, v \rangle.$$

Finally,

$$\begin{aligned} \cos \theta &= \left\langle \frac{x}{\|x\|_2}, \frac{y}{\|y\|_2} \right\rangle \\ &= \frac{\langle x, y \rangle}{\|x\|_2 \|y\|_2}. \end{aligned}$$

Hence,

$$\boxed{\cos \theta = \frac{\langle x, y \rangle}{\|x\|_2 \|y\|_2}.$$

In particular,

$$\langle x, y \rangle = 0 \iff \cos \theta = 0 \iff \theta = \frac{\pi}{2}.$$

Therefore,

$$\boxed{x \perp y \iff \langle x, y \rangle = 0.}$$

Therefore,

$$\boxed{\langle x, y \rangle = 0 \iff x \perp y.}$$

Cauchy–Schwarz

$$|\langle x, y \rangle| \leq \|x\|_2 \|y\|_2.$$

For every $t \in \mathbb{R}$,

$$0 \leq \|tx + y\|_2^2.$$

Expanding,

$$\begin{aligned} 0 &\leq \langle tx + y, tx + y \rangle \\ &= t^2 \|x\|_2^2 + 2t \langle x, y \rangle + \|y\|_2^2. \end{aligned}$$

This quadratic polynomial must be nonnegative for every t .

Therefore its discriminant satisfies

$$(2\langle x, y \rangle)^2 - 4\|x\|_2^2 \|y\|_2^2 \leq 0.$$

Hence

$$\langle x, y \rangle^2 \leq \|x\|_2^2 \|y\|_2^2,$$

so

$$|\langle x, y \rangle| \leq \|x\|_2 \|y\|_2.$$

Euclidean Norm

The inner product immediately gives a notion of length:

$$\|x\|_2 = \sqrt{\langle x, x \rangle} = \sqrt{x_0^2 + \cdots + x_{n-1}^2}.$$

Then

$$\cos \theta = \frac{\langle x, y \rangle}{\|x\|_2 \|y\|_2}.$$

Now return to compression for a second:

If two vectors x and $\tilde{x}$ are supposed to be close, a natural error is

$$\|x - \tilde{x}\|_2.$$

Similarly, for matrices we will want quantities such as

$$\|W - B\|.$$

So norms are exactly what we need to make “close” mathematically precise.

General Norm

Now abstract away from ℓ_2 .

A norm is a function

$$\|\cdot\| : V \rightarrow [0, \infty)$$

satisfying:

1. Positivity

$$\|x\| \geq 0, \quad \|x\| = 0 \iff x = 0.$$

2. Homogeneity

$$\|\alpha x\| = |\alpha| \|x\|.$$

3. Triangle inequality

$$\boxed{\|x + y\| \leq \|x\| + \|y\|}.$$

Then show why ℓ_2 satisfies triangle inequality:

$$\|x + y\|_2^2 = \|x\|_2^2 + 2\langle x, y \rangle + \|y\|_2^2.$$

By Cauchy–Schwarz,

$$\begin{aligned} &\leq \|x\|_2^2 + 2\|x\|_2\|y\|_2 + \|y\|_2^2 \\ &= (\|x\|_2 + \|y\|_2)^2. \end{aligned}$$

Therefore,

$$\boxed{\|x + y\|_2 \leq \|x\|_2 + \|y\|_2}.$$

Other Norms We Will Need

For a vector,

$$\begin{aligned} \|x\|_1 &= \sum_j |x_j|, \\ \|x\|_2 &= \left(\sum_j x_j^2 \right)^{1/2}, \\ \|x\|_\infty &= \max_j |x_j|. \end{aligned}$$

For a matrix,

$$\|A\|_F = \left(\sum_{j,k} A_{jk}^2 \right)^{1/2}$$

is the Frobenius norm.