What Is a Vector Norm?

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A vector norm measures the size, or length, of a vector. For complex *n*-vectors, a vector norm is a function $\|\cdot\|: \mathbb{C}^n \to \mathbb{R}$ satisfying

- $||x|| \ge 0$ with equality if and only if x = 0,
- $\|\alpha x\| = |\alpha| \|x\|$ for all $\alpha \in \mathbb{C}$, $x \in \mathbb{C}^n$,
- $||x+y|| \le ||x|| + ||y||$ for all $x, y \in \mathbb{C}^n$ (the triangle inequality).

An important class of norms is the Hölder p-norms

$$||x||_p = \left(\sum_{i=1}^n |x_i|^p\right)^{1/p}, \quad p \ge 1.$$
 (1)

The ∞ -norm is interpreted as $\lim_{p\to\infty} \|x\|_p$ and is given by

$$||x||_{\infty} = \max_{1 \le i \le n} |x_i|.$$

Other important special cases are

$$||x||_1 = \sum_{i=1}^n |x_i|,$$
 "Manhattan" or "taxi cab" norm,
$$||x||_2 = \left(\sum_{i=1}^n |x_i|^2\right)^{1/2} = (x^*x)^{1/2},$$
 Euclidean length.

A useful concept is that of the *dual norm* associated with a given vector norm, which is defined by

$$||y||^D = \max_{x \neq 0} \frac{|x^*y|}{||x||}.$$

The maximum is attained because the definition is equivalent to $||y||^D = \max\{|x^*y| : ||x|| = 1\}$, in which we are maximizing a continuous function over a compact set. This definition immediately gives the attainable inequality

$$|x^*y| \le ||x|| \, ||y||^D, \tag{2}$$

which is the generalized Hölder inequality.

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The dual of the *p*-norm is the *q*-norm, where $p^{-1} + q^{-1} = 1$, so for the *p*-norms the inequality (2) becomes the (standard) Hölder inequality,

$$|x^*y| \le ||x||_p ||y||_q, \quad \frac{1}{p} + \frac{1}{q} = 1.$$

An important special case is the Cauchy–Schwarz inequality,

$$|x^*y| \le ||x||_2 ||y||_2.$$

The notation $||x||_0$ is used to denote the number of nonzero entries in x, even though it is not a vector norm and is not obtained from (1) with p = 0. In portfolio optimization, if x_k specifies how much to invest in stock k then the inequality $||x||_0 \le k$ says "invest in at most k stocks".

In numerical linear algebra, vector norms play a crucial role in the definition of a subordinate matrix norm, as we will explain in the next post in this series.

All norms on \mathbb{C}^n are equivalent in the sense that for any two norms $\|\cdot\|_{\alpha}$ and $\|\cdot\|_{\beta}$ there exist positive constants ν_1 and ν_2 such that

$$\nu_1 \|x\|_{\alpha} \le \|x\|_{\beta} \le \nu_2 \|x\|_{\alpha}$$
 for all $x \in \mathbb{C}^n$.

For example, it is easy to see that

$$||x||_{2} \le ||x||_{1} \le \sqrt{n} ||x||_{2},$$

$$||x||_{\infty} \le ||x||_{2} \le \sqrt{n} ||x||_{\infty},$$

$$||x||_{\infty} \le ||x||_{1} \le n ||x||_{\infty}.$$

The 2-norm is invariant under unitary transformations: if $Q^*Q = I$, then $||Qx||^2 = x^*Q^*Qx = x^*x = ||x||_2^2$.

Care must be taken to avoid overflow and (damaging) underflow when evaluating a vector p-norm in floating-point arithmetic for $p \neq 1, \infty$. One can simply use the formula $||x||_p = ||(x/||x||_\infty)||_p ||x||_\infty$, but this requires two passes over the data (the first to evaluate $||x||_\infty$). For more efficient one-pass algorithms for the 2-norm see Higham (2002, Sec. 21.8) and Harayama et al. (2021).

References

This is a minimal set of references, which contain further useful references within.

- Takeyuki Harayama, Shuhei Kudo, Daichi Mukunoki, Toshiyuki Imamura, and Daisuke Takahashi, A Rapid Euclidean Norm Calculation Algorithm that Reduces Overflow and Underflow, in Computational Science and Its Applications–ICCSA 2021, O. Gervasi et al., eds, 95–110, Springer, 2021.
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