High-Dimensional Probability and Statistics

MATH/STAT/ECE 888: Topics in Mathematical Data Science Sebastien Roch (Math+Stat) UW-Madison Fall 2021

Lecture 19 (10/20/21)

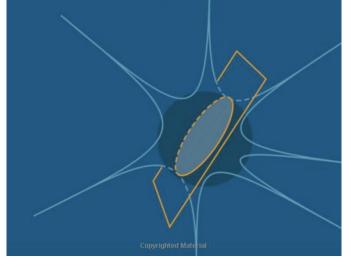
Today's slides based on Vershynin

Cambridge Series in Statistical and Probabilistic Mathematics

High-Dimensional Probability

An Introduction with Applications in Data Science

Roman Vershynin



Isometries

Distortion

The extreme singular values $s_1(A)$ and $s_n(A)$ have an important geometric meaning. They are respectively the smallest number M and the largest number m that make the following inequality true:

$$m\|x\|_{2} \le \|Ax\|_{2} \le M\|x\|_{2}$$
 for all $x \in \mathbb{R}^{n}$. (4.5)

(Check!) Applying this inequality for x - y instead of x and with the best bounds, we can rewrite it as

$$\|s_n(A)\| - y\|_2 \le \|Ax - Ay\|_2 \le s_1(A)\| - y\|_2$$
 for all $x \in \mathbb{R}^n$.

This means that the matrix A, acting as an operator from \mathbb{R}^n to \mathbb{R}^m , can only change the distance between any points by a factor that lies between $s_n(A)$ and $s_1(A)$. Thus the extreme singular values control the *distortion* of the geometry of \mathbb{R}^n under the action of A.

Isometries

Exercise 4.1.4 (Isometries). Let A be an $m \times n$ matrix with $m \ge n$. Prove that the following statements are equivalent.

- (a) $A^{\mathsf{T}}A = I_n$.
- (b) $P := AA^{\mathsf{T}}$ is an orthogonal projection¹ in \mathbb{R}^m onto a subspace of dimension n.
- (c) A is an *isometry*, or isometric embedding of \mathbb{R}^n into \mathbb{R}^m , which means that

 $||Ax||_2 = ||x||_2 \quad \text{for all } x \in \mathbb{R}^n.$

(d) All singular values of A equal 1; equivalently

$$s_n(A) = s_1(A) = 1.$$

Approximate isometries

Quite often the conditions of Exercise 4.1.4 hold only approximately, in which case we regard A as an *approximate isometry*.

Lemma 4.1.5 (Approximate isometries). Let A be an $m \times n$ matrix and $\delta > 0$. Suppose that

$$\|A^{\mathsf{T}}A - I_n\| \le \max(\delta, \delta^2).$$

Then

$$(1-\delta)\|x\|_{2} \le \|Ax\|_{2} \le (1+\delta)\|x\|_{2} \quad for \ all \ x \in \mathbb{R}^{n}.$$
(4.6)

Consequently, all singular values of A are between $1 - \delta$ and $1 + \delta$:

$$1 - \delta \le s_n(A) \le s_1(A) \le 1 + \delta.$$

$$(4.7)$$

Approximate isometries cont'd

Proof To prove (4.6), we may assume without loss of generality that $||x||_2 = 1$. (Why?) Then, using the assumption, we get

$$\max(\delta,\delta^2) \ge \left| \left\langle (A^{\mathsf{T}}A - I_n)x, x \right\rangle \right| = \left| \|Ax\|_2^2 - 1 \right|.$$

Applying the elementary inequality

$$\max(|z-1|, |z-1|^2) \le |z^2 - 1|, \quad z \ge 0$$
(4.8)

for $z = ||Ax||_2$, we conclude that

$$|||Ax||_2 - 1| \le \delta.$$

This proves (4.6), which in turn implies (4.7) as we saw in the beginning of this section.

Converse

Exercise 4.1.6 (Approximate isometries). Lemma 4.1.5: if (4.7) holds, then

$$\|A^{\mathsf{T}}A - I_n\| \le 3\max(\delta,\delta^2).$$

¹ Recall that P is a projection if $P^2 = P$, and P is called orthogonal if the image and kernel of P are orthogonal subspaces.