





Vectors and matrices

We will treat all vectors as column vectors by default. The space of real vectors of length n is denoted by \mathbb{R}^n , while the space of real-valued $m \times n$ matrices is denoted by $\mathbb{R}^{m \times n}$. That's it: ¹

$$x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x \end{bmatrix} \quad x^T = \begin{bmatrix} x_1 & x_2 & \dots & x_n \end{bmatrix} \quad x \in \mathbb{R}^n, x_i \in \mathbb{R}$$
 (1)

¹A full introduction to applied linear algebra can be found in Introduction to Applied Linear Algebra -- Vectors, Matrices, and Least Squares - book by Stephen Boyd & Lieven Vandenberghe, which is indicated in the source. Also, a useful refresher for linear algebra is in Appendix A of the book Numerical Optimization by Jorge Nocedal Stephen J. Wright.

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Similarly, if $A \in \mathbb{R}^{m \times n}$ we denote transposition as $A^T \in \mathbb{R}^{n \times m}$:

$$A = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix} \quad A^T = \begin{bmatrix} a_{11} & a_{21} & \dots & a_{m1} \\ a_{12} & a_{22} & \dots & a_{m2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1n} & a_{2n} & \dots & a_{mn} \end{bmatrix} \quad A \in \mathbb{R}^{m \times n}, a_{ij} \in \mathbb{R}$$

We will write $x \ge 0$ and $x \ne 0$ to indicate componentwise relationships

 $f \to \min_{x,y,z}$ Basic linear algebra background



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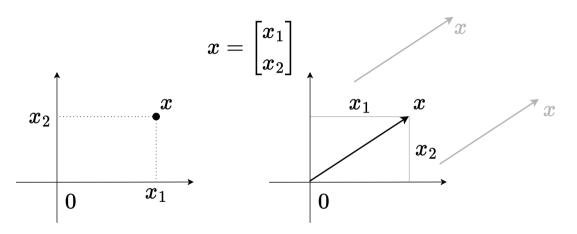


Рис. 1: Equivivalent representations of a vector

A matrix is symmetric if $A=A^T$. It is denoted as $A \in \mathbb{S}^n$ (set of square symmetric matrices of dimension n). Note, that only a square matrix could be symmetric by definition.

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Is it correct, that a positive definite matrix has all positive entries?

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Matrix product (matmul)

Let A be a matrix of size $m \times n$, and B be a matrix of size $n \times p$, and let the product AB be:

$$C = AB$$

then C is a $m \times p$ matrix, with element (i, j) given by:

$$c_{ij} = \sum_{k=1}^{n} a_{ik} b_{kj}.$$

This operation in a naive form requires $\mathcal{O}(n^3)$ arithmetical operations, where n is usually assumed as the largest dimension of matrices.

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Is it possible to multiply two matrices faster, than $\mathcal{O}(n^3)$? How about $\mathcal{O}(n^2)$, $\mathcal{O}(n)$?

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Let A be a matrix of shape $m \times n$, and x be $n \times 1$ vector, then the i-th component of the product:

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- $\langle x, Ay \rangle = \langle A^T x, y \rangle$

Norm is a qualitative measure of the smallness of a vector and is typically denoted as ||x||.

The norm should satisfy certain properties:

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The distance between two vectors is then defined as

$$d(x,y) = \|x - y\|.$$

The most well-known and widely used norm is Euclidean norm:

$$||x||_2 = \sqrt{\sum_{i=1}^n |x_i|^2},$$

which corresponds to the distance in our real life. If the vectors have complex elements, we use their modulus.

Euclidean norm, or 2-norm, is a subclass of an important class of p-norms:

$$\|x\|_p = \Big(\sum_{i=1}^n |x_i|^p\Big)^{1/p}.$$

p-norm of a vector

There are two very important special cases. The infinity norm, or Chebyshev norm is defined as the element of the maximal absolute value:

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 L_1 norm plays a very important role: it all relates to the **compressed sensing** methods that emerged in the mid-00s as one of the most popular research topics. The code for the picture below is available *here:*. Check also *this* video.

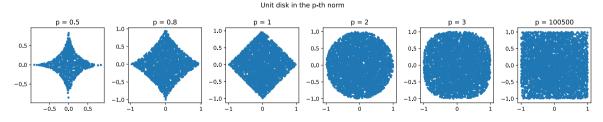


Рис. 2: Balls in different norms on a plane





Matrix norms

In some sense there is no big difference between matrices and vectors (you can vectorize the matrix), and here comes the simplest matrix norm **Frobenius** norm:

$$\|A\|_F = \left(\sum_{i=1}^m \sum_{j=1}^n |a_{ij}|^2\right)^{1/2}$$

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Spectral norm, $||A||_2$ is one of the most used matrix norms (along with the Frobenius norm).

$$||A||_2 = \sup_{x \neq 0} \frac{||Ax||_2}{||x||_2},$$

It can not be computed directly from the entries using a simple formula, like the Frobenius norm, however, there are efficient algorithms to compute it. It is directly related to the **singular value decomposition** (SVD) of the matrix. It holds

$$\|A\|_2 = \sigma_1(A) = \sqrt{\lambda_{\max}(A^TA)}$$

where $\sigma_1(A)$ is the largest singular value of the matrix A.

Scalar product

The standard scalar (inner) product between vectors x and y from \mathbb{R}^n is given by

$$\langle x, y \rangle = x^T y = \sum_{i=1}^n x_i y_i = y^T x = \langle y, x \rangle$$

Here x_i and y_i are the scalar i-th components of corresponding vectors.

- i Example
- Prove, that you can switch the position of a matrix inside a scalar product with transposition: $\langle x,Ay\rangle=\langle A^Tx,y\rangle$ and $\langle x,yB\rangle=\langle xB^T,y\rangle$

 $f \to \min_{x,y,z}$ Basic linear algebra background

Matrix scalar product

The standard scalar (inner) product between matrices X and Y from $\mathbb{R}^{m\times n}$ is given by

$$\langle X,Y\rangle = \operatorname{tr}(X^TY) = \sum_{i=1}^m \sum_{i=1}^n X_{ij} Y_{ij} = \operatorname{tr}(Y^TX) = \langle Y,X\rangle$$

Is there any connection between the Frobenious norm $\|\cdot\|_F$ and scalar product between matrices $\langle\cdot,\cdot\rangle$?

Eigenvectors and eigenvalues

A scalar value λ is an eigenvalue of the $n \times n$ matrix A if there is a nonzero vector q such that

$$Aq = \lambda q$$
.

he vector q is called an eigenvector of A. The matrix A is nonsingular if none of its eigenvalues are zero. The eigenvalues of symmetric matrices are all real numbers, while nonsymmetric matrices may have imaginary eigenvalues. If the matrix is positive definite as well as symmetric, its eigenvalues are all positive real numbers.

Eigenvectors and eigenvalues

i Theorem

$$A\succeq (\succ)0\Leftrightarrow {\sf all}\ {\sf eigenvalues}\ {\sf of}\ A\ {\sf are}\ \ge (>)0$$

- i Proof
 - 1. \rightarrow Suppose some eigenvalue λ is negative and let x denote its corresponding eigenvector. Then

$$Ax = \lambda x \to x^T A x = \lambda x^T x < 0$$

- which contradicts the condition of $A \succeq 0$.

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which contradicts the condition of $A \succeq 0$. 2. \leftarrow For any symmetric matrix, we can pick a set of eigenvectors v_1, \dots, v_n that form an orthogonal basis of \mathbb{R}^n . Pick any $x \in \mathbb{R}^n$.

$$\begin{split} \boldsymbol{x}^T A \boldsymbol{x} &= (\alpha_1 \boldsymbol{v}_1 + \ldots + \alpha_n \boldsymbol{v}_n)^T A (\alpha_1 \boldsymbol{v}_1 + \ldots + \alpha_n \boldsymbol{v}_n) \\ &= \sum \alpha_i^2 \boldsymbol{v}_i^T A \boldsymbol{v}_i = \sum \alpha_i^2 \lambda_i \boldsymbol{v}_i^T \boldsymbol{v}_i \geq 0 \end{split}$$

here we have used the fact that $v_i^T v_i = 0$, for $i \neq j$.

Eigendecomposition (spectral decomposition)

Suppose $A \in S_n$, i.e., A is a real symmetric $n \times n$ matrix. Then A can be factorized as

$$A = Q\Lambda Q^T,$$

 $^{^{2}\}mbox{A}$ good cheat sheet with matrix decomposition is available at the NLA course website.

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We usually order the eigenvalues as $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_n$. We use the notation $\lambda_i(A)$ to refer to the i-th largest eigenvalue of $A \in S$. We usually write the largest or maximum eigenvalue as $\lambda_1(A) = \lambda_{\max}(A)$, and the least or minimum eigenvalue as $\lambda_n(A) = \lambda_{\min}(A)$.

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Eigenvalues

The largest and smallest eigenvalues satisfy

$$\lambda_{\min}(A) = \inf_{x \neq 0} \frac{x^T A x}{x^T x}, \qquad \lambda_{\max}(A) = \sup_{x \neq 0} \frac{x^T A x}{x^T x}$$



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$$\kappa(A) = \|A\| \|A^{-1}\|$$



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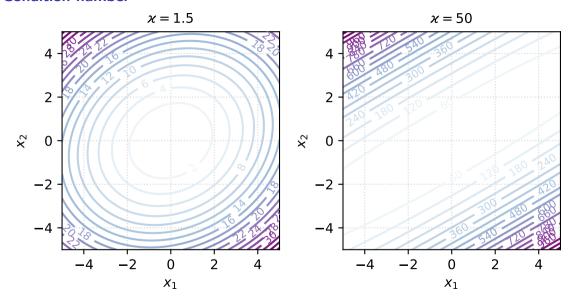
$$\kappa(A) = ||A|| ||A^{-1}||$$

If we use spectral matrix norm, we can get:

$$\kappa(A) = \frac{\sigma_{\max}(A)}{\sigma_{\min}(A)}$$

If, moreover, $A\in\mathbb{S}^n_{++}$: $\kappa(A)=rac{\lambda_{\max}(A)}{\lambda_{\min}(A)}$

Condition number







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This factorization is called the singular value decomposition (SVD) of A. The columns of U are called left singular vectors of A, the columns of V are right singular vectors, and the numbers σ_i are the singular values. The singular value decomposition can be written as

$$A = \sum_{i=1}^{r} \sigma_i u_i v_i^T,$$

where $u_i \in \mathbb{R}^m$ are the left singular vectors, and $v_i \in \mathbb{R}^n$ are the right singular vectors.

i Question

Suppose, matrix $A \in \mathbb{S}^n_{++}$. What can we say about the connection between its eigenvalues and singular values?



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i Question

How do the singular values of a matrix relate to its eigenvalues, especially for a symmetric matrix?





Basic linear algebra background

Simple, yet very interesting decomposition is Skeleton decomposition, which can be written in two forms:

$$A = UV^T \quad A = \hat{C}\hat{A}^{-1}\hat{R}$$





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• Model reduction, data compression, and speedup of computations in numerical analysis: given rank-r matrix with $r \ll n, m$ one needs to store $\mathcal{O}((n+m)r) \ll nm$ elements.

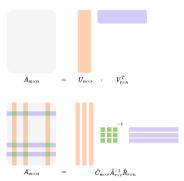


Рис. 3: Illustration of Skeleton decomposition



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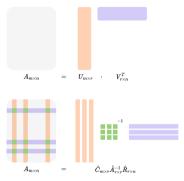


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- All applications where SVD applies, since Skeleton decomposition can be transformed into truncated SVD form.

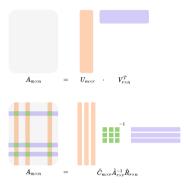


Рис. 3: Illustration of Skeleton decomposition

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Canonical tensor decomposition

One can consider the generalization of Skeleton decomposition to the higher order data structure, like tensors, which implies representing the tensor as a sum of r primitive tensors.

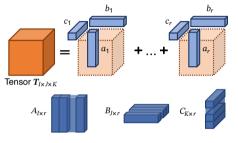


Рис. 4: Illustration of Canonical Polyadic decomposition

i Example

Note, that there are many tensor decompositions: Canonical, Tucker, Tensor Train (TT), Tensor Ring (TR), and others. In the tensor case, we do not have a straightforward definition of *rank* for all types of decompositions. For example, for TT decomposition rank is not a scalar, but a vector.

The determinant and trace can be expressed in terms of the eigenvalues

$$\mathrm{det} A = \prod_{i=1}^n \lambda_i, \qquad \mathrm{tr} A = \sum_{i=1}^n \lambda_i$$

The determinant has several appealing (and revealing) properties. For instance,

• det A = 0 if and only if A is singular;



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Basic linear algebra background

• $\det A^{-1} = \frac{1}{\det A}.$



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Don't forget about the cyclic property of a trace for arbitrary matrices A,B,C,D (assuming, that all dimensions are consistent):

$$tr(ABCD) = tr(DABC) = tr(CDAB) = tr(BCDA)$$



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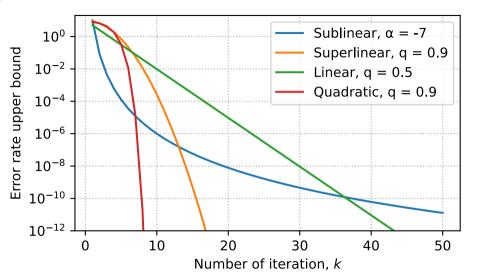
- i Question
- How does the determinant of a matrix relate to its invertibility?

Convergence rates





Convergence rate





Linear convergence

To compare the performance of algorithms, we must define the terminology for different types of convergence. Let r_{ν} be a sequence of non-negative real numbers that converges to zero. Typically, we have an iterative method producing a sequence of iterates x_k approaching the optimal solution x^* , and $r_k = \|x_k - x^*\|_2$.

The **linear convergence** of r_k is defined as follows:

A sequence $\{r_k\}_{k=m}^{\infty}$ converges linearly with a parameter 0 < q < 1 if there exists a constant C > 0 such that:

$$r_k \le Cq^k$$
, for all $k \ge m$.

If such a q exists, the sequence is said to have linear convergence. The exact lower bound of all q satisfying the inequality is called the rate of linear convergence of the sequence.

Question

Suppose, you have two sequences with linear convergence rates $q_1 = 0.1$ and $q_2 = 0.7$, which one is faster?



Linear convergence

i Example

Let us have the following sequence:

$$r_k = \frac{1}{2^k}$$

One can immediately conclude, that we have a linear convergence with parameters $q=\frac{1}{2}$ and C=0.

i Question

Determine the convergence of the following sequence

$$r_k = \frac{3}{2^k}$$

Sublinear convergence

If the sequence r_k converges to zero, but does not have linear convergence, the convergence is said to be sublinear. Sometimes we can consider the following class of sublinear convergence:

$$\|x_{k+1} - x^*\|_2 \leq C k^q,$$

where q < 0 and $0 < C < \infty$. Informally, sublinear convergence means the sequence converges slower than any geometric progression.



Superlinear convergence

A sequence $\{r_k\}_{k=m}^{\infty}$ is said to have **superlinear convergence** if it converges to zero faster than any linearly convergent sequence. Verify, that a sequence $\{r_k\}_{k=m}^{\infty}$ is superlinear if it converges linearly with the rate q=0.

For p>1, a sequence has superlinear convergence of order p if there exists C>0 and 0< q<1 such that:

$$r_k \le Cq^{p^k}, \quad \text{for all } k \ge m.$$

When p=2, this is called **quadratic convergence**.



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i Illustrative Example

Suppose $x^* = 1.23456789$ (the true solution), and the iterative sequence starts with an error $r_k = 10^{-3}$, corresponding to 3 correct significant digits (1.234).

1. After the first iteration:

$$r_{k+1} \approx r_k^2 = (10^{-3})^2 = 10^{-6}$$
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Now the error is 10^{-6} , and we have 6 correct digits (1.23456).

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2. After the second iteration:

$$r_{k+2}\approx r_{k+1}^2=(10^{-6})^2=10^{-12}.$$

Now the error is 10^{-12} , and we have 12 correct digits (1.234567890123).



Convergence rates practical observations:

• $\|x_{k+1}-x^*\|_2 \leq \frac{1}{k^{\frac{1}{p}}}\|x_0-x^*\|_2$ implies sublinear convergence rate



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- $\|x_{k+1}-x^*\|_2 \leq \frac{1}{L^{\frac{1}{n}}}\|x_0-x^*\|_2$ implies sublinear convergence rate
- $||x_{k+1} x^*||_2 \le q ||x_k x^*||_2$ implies linear convergence rate, where q < 1

Convergence rates practical observations:

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- $\|x_{k+1}-x^*\|_2 \leq q\|x_k-x^*\|_2$ implies linear convergence rate, where q<1 $\|x_{k+1}-x^*\|_2 \leq q\|x_k-x^*\|_2^2$ implies quadratic convergence rate, where $q\|x_0-x^*\|<1$

Root test

i Theorem

Let $(r_k)_{k=m}^{\infty}$ be a sequence of non-negative numbers converging to zero, and let $\alpha:=\limsup_{k\to\infty}r_k^{1/k}$. (Note that $\alpha \geq 0$.) (a) If $0 \le \alpha < 1$, then $(r_k)_{k=m}^{\infty}$ converges linearly with constant α .

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1. let us show that if $(r_k)_{k=m}^\infty$ converges linearly with constant $0 \le \beta < 1$, then necessarily $\alpha \le \beta$. Indeed, by the definition of the constant of linear convergence, for any $\varepsilon > 0$ satisfying $\beta + \varepsilon < 1$, there exists C > 0 such that $r_k \le C(\beta + \varepsilon)^k$ for all $k \ge m$. From this, $r_k^{1/k} \le C^{1/k}(\beta + \varepsilon)$ for all $k \ge m$. Passing to the limit as $k \to \infty$ and using $C^{1/k} \to 1$, we obtain $\alpha < \beta + \varepsilon$. Given the arbitrariness of ε , it follows that $\alpha < \beta$.

 $f \to \min_{x,y,z}$

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- (a) If $0 \le \alpha < 1$, then $(r_k)_{k=m}^{\infty}$ converges linearly with constant α .
- (b) In particular, if $\alpha=0$, then $(r_k)_{k=m}^{\infty}$ converges superlinearly.
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- 2. Thus, in the case $\alpha=1$, the sequence $(r_k)_{k=m}^\infty$ cannot have linear convergence according to the above result (proven by contradiction). Since, nevertheless, $(r_k)_{k=m}^\infty$ converges to zero, it must converge sublinearly.

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1. Now consider the case $0 \le \alpha < 1$. Let $\varepsilon > 0$ be an arbitrary number such that $\alpha + \varepsilon < 1$. According to the properties of the limsup, there exists $N \ge m$ such that $r_k^{1/k} \le \alpha + \varepsilon$ for all $k \ge N$. Hence, $r_k \le (\alpha + \varepsilon)^k$ for all $k \ge N$. Therefore, $(r_k)_{k=m}^\infty$ converges linearly with parameter $\alpha + \varepsilon$ (it does not matter that the inequality is only valid from the number N). Due to the arbitrariness of ε , this means that the constant of linear convergence of $(r_k)_{k=m}^\infty$ does not exceed α . Since, as shown above, the constant of linear convergence cannot be less than α , this means that the constant of linear convergence of $(r_k)_{k=m}^\infty$ is exactly α .

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- 2. Finally, let's show that the case $\alpha > 1$ is impossible. Indeed, suppose $\alpha > 1$. Then from the definition of limsup, it follows that for any $N \ge m$, there exists $k \ge N$ such that $r_k^{1/k} \ge 1$, and, in particular, $r_k \ge 1$. But this means that r_k has a subsequence that is bounded away from zero. Hence, $(r_k)_{k=1}^{\infty}$ cannot converge to zero, which contradicts the condition.



Let $\{r_k\}_{k=m}^{\infty}$ be a sequence of strictly positive numbers converging to zero. Let

$$q = \lim_{k \to \infty} \frac{r_{k+1}}{r_k}$$

• If there exists q and $0 \le q < 1$, then $\{r_k\}_{k=m}^{\infty}$ has linear convergence with constant q.



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- If $\lim_{k \to \infty} \inf_k \frac{r_{k+1}}{r_k} = 1$, then $\{r_k\}_{k=m}^\infty$ has sublinear convergence.
- \bullet The case $\lim_{k\to\infty}\inf_k\frac{r_{k+1}}{r_{\iota_{\cdot}}}>1$ is impossible.
- In all other cases (i.e., when $\lim_{k \to \infty} \inf_k \frac{r_{k+1}}{r_{L}} < 1 \le \lim_{k \to \infty} \sup_k \frac{r_{k+1}}{r_{L}}$) we cannot claim anything concrete about the convergence rate $\{r_k\}_{k=m}^{\infty}$.



Ratio test lemma

i Theorem

Let $(r_k)_{k=m}^{\infty}$ be a sequence of strictly positive numbers. (The strict positivity is necessary to ensure that the ratios $\frac{r_{k+1}}{r}$, which appear below, are well-defined.) Then

$$\liminf_{k\to\infty}\frac{r_{k+1}}{r_k}\leq \liminf_{k\to\infty}r_k^{1/k}\leq \limsup_{k\to\infty}r_k^{1/k}\leq \limsup_{k\to\infty}\frac{r_{k+1}}{r_k}.$$

Proof.

1. The middle inequality follows from the fact that the liminf of any sequence is always less than or equal to its limsup. Let's prove the last inequality; the first one is proved analogously.

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- 2. Denote $L:=\limsup_{k\to\infty}\frac{r_{k+1}}{r_k}$. If $L=+\infty$, then the inequality is obviously true, so let's assume L is finite. Note that $L\geq 0$, since the ratio $\frac{r_{k+1}}{r_k}$ is positive for all $k\geq m$. Let $\varepsilon>0$ be an arbitrary number. According to the properties of limsup, there exists $N\geq m$ such that $\frac{r_{k+1}}{r_k}\leq L+\varepsilon$ for all $k\geq N$. From here, $r_{k+1}\leq (L+\varepsilon)r_k$ for all $k\geq N$. Applying induction, we get $r_k\leq (L+\varepsilon)^{k-N}r_N$ for all $k\geq N$. Let $C:=(L+\varepsilon)^{-N}r_N$. Then $r_k\leq C(L+\varepsilon)^k$ for all $k\geq N$, from which $r_k^{1/k}\leq C^{1/k}(L+\varepsilon)$. Taking the limsup as $k\to\infty$ and using $C^{1/k}\to 1$, we get $\limsup_{k\to\infty}r_k^{1/k}\leq L+\varepsilon$. Given the arbitrariness of ε , it follows that $\limsup_{k\to\infty}r_k^{1/k}\leq L$.



Summary



Summary



Summary

Определения

- 1. Положительно определённая матрица.
- 2. Евклидова норма вектора.
- 3. Неравенство треугольника для нормы.
- р-норма вектора.
- 5. Как выглядит единичный шар в p норме на плоскости для $p = 1, 2, \infty$?
- 6. Норма Фробениуса для матрицы. 7. Спектральная норма матрицы.
- Скалярное произведение двух векторов. 9. Скалярное произведение двух матриц,
- согласованное с нормой Фробениуса. 10. Собственные значения матрицы. Спектр матрицы.
- 11. Связь спектра матрицы и её определенности.
- 12. Спектральное разложение матрицы.
- 13. Сингулярное разложение матрицы.
- 14. Связь определителя и собственных чисел для квадратной матрицы. 15. Связь следа и собственных чисел для квадратной

- 16. Линейная сходимость последовательности.
- 17. Сублинейная сходимость последовательности.
- 18. Сверхлинейная сходимость последовательности. 19. Квадратичная сходимость последовательности.
- 20. Тест корней для определения скорости сходимости последовательности.
- 21. Тест отношений для определения скорости сходимости последовательности.

Теоремы

- 1. Критерий положительной определенности матрицы через знаки собственных значений матрицы.
- 2. Тест корней
- 3. Тест отношений

