Numerical Analysis Lecture Notes

Rebekah Dix

October 7, 2018

Contents

1 Results from Real Analysis

Theorem 1. *(The Mean Value Theorem) Suppose f is a real-valued function, defined and continuous on the closed interval $[a, b] \in \mathbb{R}$ and f differentiable on the open interval (a, b). Then there exists a number $\xi \in (a, b)$ such that*

$$f(b) - f(a) = f'(\xi)(b - a) \tag{1}$$

2 Solution of equations by iteration

Theorem 2. *(Existence of Root) Let f be a real-valued function, defined and continuous on a bounded closed interval $[a, b]$ of the real line. Assume further, that $f(a)f(b) \leq 0$; then, there exists ξ in $[a, b]$ such that $f(\xi) = 0$.*

Proof. The condition $f(a)f(b) \leq 0$ implies that $f(a)$ and $f(b)$ have opposite signs, or one of them is 0. If either $f(a)$ or $f(b)$ is 0, then we've found a root. Suppose that both endpoints are non-zero (in which case they have opposite signs). In this case, 0 must belong to the open interval whose endpoints are $f(a)$ and $f(b)$. The intermediate value theorem gives the existence of a root in the open interval (a, b). Thus, in both cases, a zero is guaranteed. □

- The converse of Theorem 2 is clearly false.

Theorem 3. *(Brouwer's Fixed Point Theorem) Suppose that g is a real-valued function, defined and continuous on a bounded closed interval $[a, b]$ of the real line, and let $g(x) \in [a, b]$ for all $x \in [a, b]$. Then, there exists $\xi \in [a, b]$ such that $\xi = g(\xi)$. ξ is called a fixed point of the function g.*

Proof. Define a function $f(x) = x - g(x)$. If we find a root ξ of f, then ξ is a fixed point of g. Then,

$$f(a)f(b) = (a - g(a))(b - g(b)) \leq 0 \tag{2}$$

By assumption, $a \leq g(a), g(b) \leq b$. Therefore, the first term is negative and the second term is positive. Therefore, $f(a)f(b) \leq 0$. By Theorem 2, there exists a $\xi \in [a, b]$ such that $f(\xi) = 0$. Then, for this ξ, $g(\xi) = \xi$. □

Definition 1. *(Simple Iteration) Suppose that g is a real-valued function, defined and continuous on a bounded closed interval $[a, b]$ of the real line, and let $g(x) \in [a, b]$ for all $x \in [a, b]$. Given that $x_0 \in [a, b]$, the recursion defined by*

$$x_{k+1} = g(x_k) \tag{3}$$

is called simple iteration; the numbers x_k, $k \geq 0$, are referred to as iterates.

- If this sequence converges, the limit must be a fixed of g, since g is continuous on a closed interval. Note that

$$\xi = \lim_{k \to \infty} x_{k+1} = \lim_{k \to \infty} g(x_k) = g\left(\lim_{k \to \infty} x_k\right) = g(\xi) \tag{4}$$

Definition 2. *(Contraction) Let g be a real-valued function, defined and continuous on a bounded closed interval $[a, b]$ of the real line. Then, g is said to be a contraction on $[a, b]$ if there exists a constant L such that $0 < L < 1$ and*

$$|g(x) - g(y)| \leq L|x - y| \quad \forall x, y \in [a, b] \tag{5}$$

Theorem 4. *(Contraction Mapping Theorem) Suppose that g is a real-valued function, defined and continuous on a bounded closed interval $[a, b]$ of the real line, and let $g(x) \in [a, b]$ for all $x \in [a, b]$. Suppose g is a contraction on $[a, b]$. Then, g has a unique fixed point ξ in the interval $[a, b]$. Moreover, the sequence (x_k) defined by simple iteration converges to ξ as $k \to \infty$ for any starting value x_0 in $[a, b]$.*

Let $\epsilon > 0$ be a certain tolerance, and let $k_0(\epsilon)$ denote the smallest positive integer such that x_k is no more than ϵ away from the fixed point ξ (i.e. $|x_k - \xi| \leq \epsilon$) for all $k \geq k_0(\epsilon)$. Then,

$$k_0(\epsilon) \leq \left\lfloor \frac{\ln|x_1 - x_0| - \ln(\epsilon(1 - L))}{\ln(1/L)} \right\rfloor + 1 \tag{6}$$

Proof. Let $E_k = |x_k - \xi|$ be the error at k. Then

$$\begin{aligned} |x_{k+1} - \xi| &= |g(x_k) - g(\xi)| \\ &< L|x_k - \xi| \end{aligned}$$

Therefore

$$E_k \leq L^k E_0 \tag{7}$$

Since $L < 1$, $L^k \to 0$ as $k \to \infty$. □

Definition 3. *(Stable, Unstable Fixed Point) Suppose that g is a real-valued function, defined and continuous on a bounded closed interval $[a, b]$ of the real line, and let $g(x) \in [a, b]$ for all $x \in [a, b]$, and let ξ denote a fixed point of g. ξ is a stable fixed point of g if the sequence (x_k) defined by the iteration $x_{k+1} = g(x_k)$, $k \geq 0$, converges to ξ whenever the starting value x_0 is sufficiently close to ξ. Conversely, if no sequence (x_k) defined by this iteration converges to ξ for any starting value x_0 close to ξ, except for $x_0 = \xi$, then we say that ξ is an unstable fixed point of g.*

- With this definition, a fixed point may be neither stable nor unstable.

Definition 4. *(Rate of Convergence) Suppose $\xi = \lim_{k \to \infty} x_k$. Define $E_k = |x_k - \xi|$.*

- The sequence (x_k) converges to ξ linearly if there exists a number $\mu \in (0,1)$ such that

$$\lim_{k\to\infty} \frac{E_{k+1}}{E_k} = \mu \tag{8}$$

- The sequence (x_k) converges to ξ superlineraly if $\mu = 0$. That is, the sequence of μ_k generated at each step $\to 0$ as $k \to \infty$.

- The sequence (x_k) converges to ξ with order q if there exists a $\mu > 0$ such that

$$\lim_{k\to\infty} \frac{E_{k+1}}{E_k^q} = \mu \tag{9}$$

  In particular, if $q = 2$, then the sequence converges quadratically.

2.1 Newton's Method

Definition 5. *(Newton's Method) Newton's method for the solution of $f(x) = 0$ is defined by*

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)} \tag{10}$$

Geometrically, $(x_{n+1}, 0)$ is the intersection of the x-axis and the tangent of the graph of f at $(x_n, f(x_n))$.

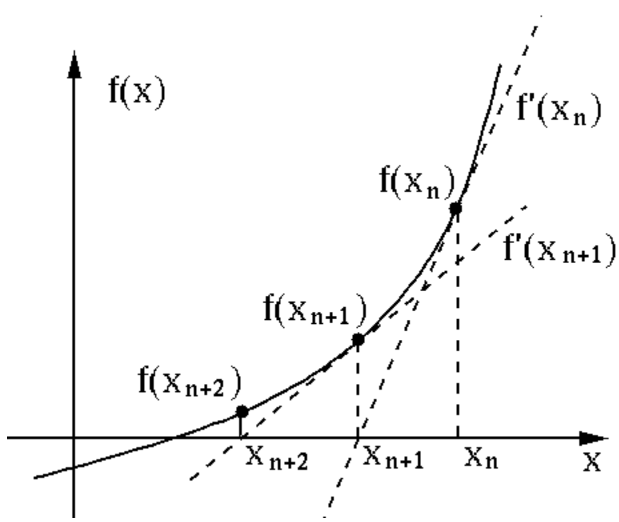

Figure 1: Geometric Interpretation of Newton's Method in $\mathbb{R}$

2.2 Secant Method

Observe that Newton's method requires us to know the first derivative f' of f. In applications, we might not know f' or it could be expensive to calculate. This motivates approximating the $f'(x_k)$ in Newton's method with

$$f'(x_k) \approx \frac{f(x_k) - f(x_{k-1})}{x_k - x_{k-1}} \tag{11}$$

Definition 6. *(Secant Method) The secant method is defined by*

$$x_{k+1} = x_k - f(x_k)\frac{x_k - x_{k-1}}{f(x_k) - f(x_{k-1})} \tag{12}$$

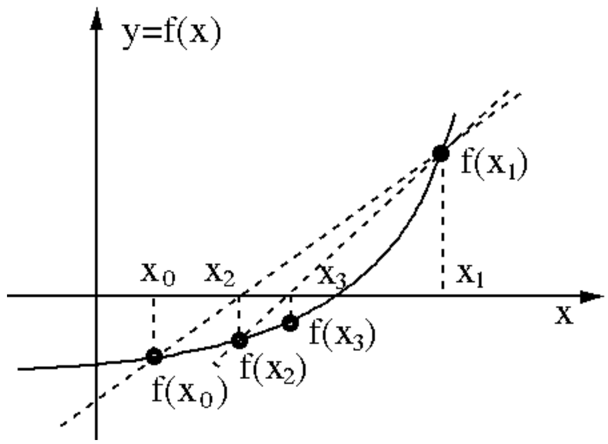

Figure 2: Geometric Interpretation of Secant Method in $\mathbb{R}$

Theorem 5. *(Convergence of Secant Method) Suppose that f is a real-valued function, defined and continuously differentiable on an interval $I = [\xi - h, \xi + h]$, $h > 0$, with center point ξ. Suppose further that $f(\xi) = 0$, $f'(\xi) \neq 0$. Then, the sequence (x_k) defined by the secant method converges at least linearly to ξ provided that x_0 and x_1 are sufficiently close to ξ.*

Proof. $\square$

3 Solution of systems of linear equations

3.1 Least Squares

Given a system of equations $Ax = b$, the least squares problem is

$$\min_{x \in \mathbb{R}^n} \|Ax - b\|_2^2 \tag{13}$$

We can expand the objective function out as

$$\begin{aligned}\|Ax-b\|_2^2 &= (Ax-b)^T(Ax-b) \\ &= x^TA^TAx - 2b^TAx + b^Tb\end{aligned}$$

To find the x that minimizes this expression we find the x that satisfies $\nabla_x F = 0$. That is

$$\nabla_x F = 0 = 2A^TAx - 2A^Tb \tag{14}$$

Therefore the minimizer is $x = (A^TA)^{-1}A^Tb$. $(A^TA)^{-1}A^T$ is called the pseudo-inverse of A. If A is square and invertible, then the pseudo-inverse equals A^{-1}.

3.2 Gram-Schimdt Orthogonalization

Algorithm: Denote the columns of A by a_i.

1. $q_1 = a_1$. Then normalized by $q_1 = \frac{q_1}{\|q_1\|}$.
2. $q_2 = a_2 - \langle q_1, a_2\rangle q_1$. Then normalize by $q_2 = \frac{q_2}{\|q_2\|}$. It's simple to verify that $q_2 \perp q_1$.
3. For an arbitrary k, $q_k = a_k - \langle a_k, q_1\rangle q_1 - \langle a_k, q_2\rangle q_2 - \ldots - \langle a_k, q_{k-1}\rangle q_{k-1}$. Then normalize by $q_k = \frac{q_k}{\|q_k\|}$.

We can observe the following properties:

1. $\|q_i\| = 1$ (this follows directly)
2. $q_i \perp q_j$ for all $i \neq j$
3. $q_k \in span(a_1, \ldots, a_k)$ and $a_k \in span(q_1, \ldots, q_k)$ so that $span(a_1, \ldots, a_k) = span(q_1, \ldots, q_k)$.

[[Write proof for 2]].

3.3 QR Factorization

Definition 7. *(Unitary Matrix) A matrix $Q = [q_1 \ldots q_n] \in \mathbb{R}^{m\times n}$ is unitary if and only if $\langle q_i, q_j\rangle = \delta_{ij}$.*

Observations about this definition:

1. $Q^TQ = I$
2. If Q is square, then $Q^T = Q^{-1}$.

3.3.1 Application to Least Squares

Suppose that we can write $A = QR$, where $A \in \mathbb{R}^{m\times n}$, $Q \in \mathbb{R}^{m\times n}$ and unitary, and $R \in \mathbb{R}^{n\times n}$ and upper triangular. Then the least squares solution to $Ax = b$ is given by

$$\begin{aligned}
x &= (A^T A)^{-1} A^T b \\
&= (R^T Q^T Q R)^{-1} R^T Q^T b \\
&= (R^T R)^{-1} R^T Q^T b \\
\implies (R^T R)x &= R^T Q^T b \\
Rx &= Q^T b \qquad \text{(assume } R \text{ is invertible (i.e. no zeros on the diagonal))}
\end{aligned}$$

We can then solve for x using back substitution, which is $\mathcal{O}(n^2)$.

3.4 Norms and Condition Numbers

Definition 8. *(Norm) Suppose that $\mathcal{V}$ is a linear space over the field $\mathbb{R}$. The nonnegative real-valued function $\|\cdot\|$ is a norm on $\mathcal{V}$ if the following axioms are satisfied: Fix $v \in \mathcal{V}$*

1. *Positivity: $\|v\| = 0$ if and only if $v = 0$*
2. *Scale Preservation: $\|\alpha v\| = |\alpha|\|v\|$ for all $\alpha \in \mathbb{R}$*
3. *Triangle Inequality: $\|v + w\| \leq \|v\| + \|w\|$.*

Example 1. (Examples of Norms)

1. 1-norm:
$$\|v\|_1 = \sum_{i=1}^{n} |v_i| = |v_1| + \cdots + |v_n| \tag{15}$$
2. 2-norm:
$$\|v\|_2 = \left(\sum_{i=1}^{n} v_i^2\right)^{\frac{1}{2}} = \sqrt{v_1^2 + \cdots + v_n^2} = \sqrt{v^T v} \tag{16}$$
3. ∞-norm
$$\|x\|_\infty = \max_{i=1,\ldots,n} |v_i| \tag{17}$$
4. p-norm
$$\|v\|_p = \left(\sum_{i=1}^{n} |v_i|^p\right)^{\frac{1}{p}} \tag{18}$$

   For the p-norm, proving the triangle inequality follows from the Minkowski's inequality.

Definition 9. *(Operator Norm) Let A be an $m \times n$ matrix. That is, A is a linear transformation form $\mathbb{R}^n$ to $\mathbb{R}^m$. Then the operator norm (or subordinate matrix norm) of A is*

$$\|A\|_{p,q} = \sup_{x \in \mathbb{R}^n, x \neq 0} \frac{\|Ax\|_q}{\|x\|_p}. \tag{19}$$

Observations about this definition:

1. It's easy to check that this definition of the operator norm satisfies the properties of a norm given in Definition 8. For the triangle inequality, observe that

$$\begin{aligned} \|(A+B)x\|_p &\leq \|Ax\|_p + \|Bx\|_p \qquad \text{(from Minkowski's inequality)} \\ \implies \frac{\|(A+B)x\|_p}{\|x\|_p} &\leq \frac{\|Ax\|_p}{\|x\|_p} + \frac{\|Bx\|_p}{\|x\|_p} \end{aligned}$$

   Taking the supremum of both sides over x shows that $\|A+B\|_p \leq \|A\|_p + \|B\|_p$.

2. The definition immediately implies that for an arbitrary $x \in \mathbb{R}^n$, $x \neq 0$,

$$\|Ax\|_q \leq \|A\|_{p,q} \|x\|_p \tag{20}$$

   We can generalize this inequality to claim that

$$\|AB\| \leq \|A\| \|B\| \tag{21}$$

   for conformable matrices A, B. Indeed, fix $0 \neq x \in R^n$. Then

$$\|ABx\| \leq \|A\| \|Bx\| \leq \|A\| \|B\| \|x\| \tag{22}$$

   We can divide all inequalities by $\|x\|$ to see that for all $x \neq 0$,

$$\frac{\|ABx\|}{\|x\|} \leq \|A\| \|B\| \tag{23}$$

   Taking the supremum over x on the left hand side shows that $\|AB\| \leq \|A\| \|B\|$.

Theorem 6. *(The 1-norm of a matrix is the largest absolute-value column sum) Let $A \in \mathbb{R}^{m \times n}$ and denote the columns of A by a_j, $j = 1, \ldots, n$. Then $\|A\|_1 = \max_{j=1,\ldots,n} \sum_{i=1}^m |a_{ij}| = \max_{j=1,\ldots,n} \|a_j\|$.*

Proof. Fix $x \in \mathbb{R}^n$. Let $C = \max_{j=1,\ldots,n} \sum_{i=1}^m |a_{ij}|$. First consider the product $A \cdot x$. The ith element is $\sum_{j=1}^{n} a_{ij}x_j$. Then

$$\begin{aligned}
\|Ax\|_1 &= \sum_{i=1}^{m} |(Ax)_i| = \sum_{i=1}^{m} |\sum_{j=1}^{n} a_{ij}x_j| \\
&\leq \sum_{i=1}^{m}\sum_{j=1}^{n} |a_{ij}||x_j| && \text{(triangle inequality)} \\
&= \sum_{j=1}^{n} |x_j| \left(\sum_{i=1}^{m} |a_{ij}|\right) && \text{(interchange order of summation, assumed finite)} \\
&\leq C\|x\|_1
\end{aligned}$$

Therefore $\frac{\|Ax\|_1}{\|x\|_1} \leq C$ for all x. Next, we find an x such we achieve equality with C. Call index J the index such that $\|a_J\|_1 = C = \max_{j=1,\ldots,n} \sum_{i=1}^{m} |a_{ij}|$. Then let e_J be the n-vector of zeros with a 1 in the Jth entry. Clearly $\|e_J\|_1 = 1$. But then

$$\|Ae_J\|_1 = \|a_J\|_1 = C \tag{24}$$

In sum, we first showed that for all $x \in \mathbb{R}^n$

$$\frac{\|Ax\|_1}{\|x\|_1} \leq C \tag{25}$$

We then found an $x \in \mathbb{R}^n$ such that $\frac{\|Ax\|_1}{\|x\|_1} = C$. Therefore

$$\|A\|_1 = \sup_{x\in\mathbb{R}^n, x\neq 0} \frac{\|Ax\|_1}{\|x\|_1} = C = \max_{j=1,\ldots,n} \sum_{i=1}^{m} |a_{ij}| = \max_{j=1,\ldots,n} \|a_j\| \tag{26}$$

□

Theorem 7. *(The ∞-norm of a matrix is the largest absolute-value row sum) Let $A \in \mathbb{R}^{m\times n}$ and denote the rows of A by b_i, $i = 1,\ldots,m$. Then $\|A\|_\infty = \max_{i=1,\ldots,m} \sum_{j=1}^{n} |a_{ij}| = \max_{i=1,\ldots,m} \|b_i\|$.*

Proof. Fix $x \in \mathbb{R}^n$. Let $C = \max_{i=1,\ldots,m} \sum_{j=1}^{n} |a_{ij}|$.

$$\begin{aligned}
\|Ax\|_\infty &= \max_{i=1,\ldots,m} |\sum_{j=1}^{n} a_{ij}x_j| \\
&\leq \max_{i=1,\ldots,m} \sum_{j=1}^{n} |a_{ij}||x_j| && \text{(by the triangle inequality)} \\
&\leq \max_{i=1,\ldots,m} \sum_{j=1}^{n} |a_{ij}|\|x\|_\infty && \text{(since } |x_j| \leq \|x\|_\infty \text{ for all } j) \\
&= C\|x\|_\infty
\end{aligned}$$

Next, we find an x such we achieve equality with C. Call I the index for which $\|b_I\|_\infty = C$. Define

$$x_j = \begin{cases} 1 & a_{Ij} > 0 \\ -1 & a_{Ij} < 0 \end{cases} \tag{27}$$

Observe that $\|x\|_\infty = 1$. Then

$$\begin{aligned} |A \cdot x|_I &= |b_I^T \cdot x| \\ &= |\sum_{j=1}^{m} a_{Ij} x_j| \\ &= |\sum_{j=1}^{m} a_{Ij}| \\ &= C \end{aligned}$$

We then found an $x \in \mathbb{R}^n$ such that $\frac{\|Ax\|_\infty}{\|x\|_\infty} = C$. Therefore

$$\|A\|_\infty = \sup_{x \in \mathbb{R}^n, x \neq 0} \frac{\|Ax\|_\infty}{\|x\|_\infty} = C = \max_{i=1,\ldots,m} \sum_{j=1}^{n} |a_{ij}| = \max_{i=1,\ldots,m} \|b_i\| \tag{28}$$

□

Theorem 8. *(The 2-norm of a symmetric positive definite matrix is the maximum absolute value of its eigenvalues) Let A be a positive definite $n \times n$ matrix. Then*

$$\|A\|_2 = \max_{i=1,\ldots,n} |\lambda_i| \tag{29}$$

Proof. Since A is positive definite, A has n distinct eigenvalues, which implies that it has n linearly independent eigenvectors. Therefore, for an arbitrary $x \in \mathbb{R}^n$, we can write x as a linearly combination of the eigenvectors $x_1, \ldots, x_n$. Then

$$\begin{aligned} x &= c_1 x_1 + \cdots + c_n x_n \\ Ax &= c_1 A x_1 + \cdots + c_n A x_n \\ &= c_1 \lambda_1 x_2 + \cdots + c_n \lambda_n x_n \end{aligned}$$

We can normalize the eigenvectors of A so that $x_i^T x_i = 1$. Then $\|Ax\|_2 = \sqrt{\sum_{i=1}^n c_i^2 \lambda_i^2}$ and $\|x\|_2 = \sqrt{\sum_{i=1}^n c_i^2}$. Therefore

$$\frac{\|Ax\|_2}{\|x\|_2} = \sqrt{\frac{\sum_{i=1}^n c_i^2 \lambda_i^2}{\sum_{i=1}^n c_i^2}} \leq \max_i |\lambda_i| = |\lambda_I| \tag{30}$$

Now we'll find an x such that we actually achieve equality. Call I the index of the maximum absolute value of an eigenvalue. Then, consider the eigenvector associated with this eigenvalue, called x_i. Then

$$\frac{\|Ax_I\|_2}{\|x_I\|_2} = \frac{|\lambda_I|\|x_I\|}{\|x_I\|} = |\lambda_I| \tag{31}$$

This shows that $\|A\|_2 = \max_i |\lambda_i|$. □

Theorem 9. *(The 2-norm of a matrix $A_{m\times n}$ equals its largest singular value) Let A be an $m \times n$ matrix and denote the eigenvalues of the matrix $B = A^T A$ by λ_i, $i = 1, \ldots, n$. Then*

$$\|A\|_2 = \max_i \sqrt{\lambda_i} \tag{32}$$

The square roots of the (nonnegative) eigenvalues of $A^T A$ are referred to as the singular values of A.

3.4.1 Conditioning

Conditioning helps us quantify the sensitivity of the output to perturbations of the input. In what follows, let f be a mapping from a subset D of a normed linear space $\mathcal{V}$ to another normed linear space $\mathcal{W}$.

Definition 10. *(Absolute Condition Number)*

$$Cond(f) = \sup_{x,y\in D, x\neq y} \frac{\|f(x) - f(y)\|}{\|x - y\|} \tag{33}$$

Definition 11. *(Absolute Local Condition Number)*

$$Cond_x(f) = \sup_{x+\delta x\in D, \delta x\neq 0} \frac{\|f(x+\delta x) - f(x)\|}{\|\delta x\|} \tag{34}$$

The previous two definitions depend on the magnitudes of $f(x)$ and x. In applications, it's often better to rescale as follows

Definition 12. *(Relative Local Condition Number)*

$$cond_x(f) = \sup_{x+\delta x\in D, \delta x\neq 0} \frac{\|f(x+\delta x) - f(x)\| / \|f(x)\|}{\|\delta x\| / \|x\|} \tag{35}$$

In these definitions, if f is differentiable then we can replace the differences with the appropriate derivatives.

Example 2. (Example of conditions numbers) Let D be a subinterval of $[0, \infty)$ and $f(x) = \sqrt{x}$. Then $f'(x) = \frac{1}{2\sqrt{x}}$.

1. If $D = [1, 2]$, then $Cond(f) = \frac{1}{2}$.

2. If $D = [0, 1]$, then $Cond(f) = \infty$.

3. If $D = (0, \infty)$, then the the absolute local condition number of f at $x \in D$ is

$$Cond_x(f) = \frac{1}{2\sqrt{x}} \tag{36}$$

   Thus as $x \rightarrow$, $Cond_x(f) \rightarrow \infty$, and as $x \rightarrow \infty$, $Cond_x(f) \rightarrow 0$.

4. If $D = (0, \infty)$, then the relative local condition number of f is $cond_x(f) = 1/2$ for all $x \in D$.

Definition 13. *(Condition Number of a Nonsingular Matrix) The condition number of a nonsingular matrix A is defined by*

$$\kappa(A) = \|A\|\|A^{-1}\| \tag{37}$$

If $\kappa(A) \gg 1$, the matrix is said to be ill-conditioned.

Observations about this definition:

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

2. For all A, $\kappa(A) \geq 1$. This follows because

$$1 = \|I\| = \|AA^{-1}\| \leq \|A\|\|A^{-1}\| \tag{38}$$

3. The condition number of a matrix is unaffected by scaling all its elements by multiplying by a nonzero constant.

4. There is a condition number for each norm, and the size of the condition number is strongly dependent on the choice of norm.

4 Special Matrices

4.1 Symmetric Positive Definite Matrices

Definition 14. *(Symmetric, Positive Definite, spd) The real matrix A is said to be symmetric if $A = A^T$. A square $n \times n$ matrix is called positive definite if*

$$\boldsymbol{x}^T A \boldsymbol{x} > 0 \tag{39}$$

for all $\boldsymbol{x} \in \mathbb{R}^n$, $\boldsymbol{x} \neq 0$.

Theorem 10. *(Properties of spd matrices) Let A be an $n \times n$ real, spd matrix. Then*

1. *$a_{ii} > 0$ for all $i = 1, \ldots, n$ (the diagonal elements of A are positive).*

2. *$Ax_i = \lambda_i x_i \implies \lambda_i \in \mathbb{R}_{>0}, \boldsymbol{x} \in \mathbb{R}^n \setminus \{0\}$ (the eigenvalues of A are real and positive, and the eigenvectors of A belong to $\mathbb{R}^n \setminus \{0\}$).*

3. *$x_i \perp x_j$ if $\lambda_i \neq \lambda_j$ (the eigenvectors of distinct eigenvalues of A are orthogonal)*

4. $\det(A) > 0$ *(the determinant of A is positive)*

5. *Every submatrix B of A obtained by deleting any set of rows and the corresponding set of columns from A is symmetric and positive definite (in particular, every principal submatrix is positive definite).*

Proof. We prove each claim in the theorem as follows

1. Let e_i be the ith canonical basis vector in $\mathbb{R}^n$. Then

$$a_{ii} = e_i^T A e_i > 0 \tag{40}$$

since A is pd. A few observations: this only relies on A being pd. $e_i^T A$ picks out the ith row of A. Ae_i picks out the ith column of A.

2. We'll first show that the eigenvalues of A are real. Suppose λ, $\boldsymbol{x}$ are an eigenvalue/vector pair of A. Thus $A\boldsymbol{x} = \lambda\boldsymbol{x}$. We can conjugate this equation to find that $\bar{A}\bar{\boldsymbol{x}} = A\bar{\boldsymbol{x}} = \bar{\lambda}\bar{x}$ (thus complex eigenvalues of real valued matrices come in conjugate pairs). Then

$$\boldsymbol{x}^T A\bar{\boldsymbol{x}} = \bar{\lambda}\boldsymbol{x}^T\bar{\boldsymbol{x}}$$
$$\boldsymbol{x}^T A^T\bar{\boldsymbol{x}} = (A\boldsymbol{x})^T\bar{\boldsymbol{x}} = \lambda\boldsymbol{x}^T\bar{\boldsymbol{x}}$$

Since $A = A^T$, we know that $\lambda\boldsymbol{x}^T\bar{\boldsymbol{x}} = \lambda\boldsymbol{x}^T\bar{\boldsymbol{x}}$. As long as $\boldsymbol{x} \neq 0$, then $\boldsymbol{x}^T\bar{\boldsymbol{x}} \neq 0$. Therefore $\bar{\lambda} = \lambda$, which shows $\lambda \in \mathbb{R}$.

The fact that the eigenvector associated with λ has real elements follows by noting that all elements of the singular matrix $A - \lambda I$ are real numbers. Therefore, the columns of $A - \lambda I$ are linearly dependent in $\mathbb{R}^n$. Hence there exists an $\boldsymbol{x} \in \mathbb{R}^n$ such that $(A - \lambda I)\boldsymbol{x} = 0$.

This proof only requires that A is symmetric – therefore any real, symmetric matrix has real eigenvalues/vectors.

Next we'll show the eigenvalues of A are positive. Suppose λ, $\boldsymbol{x}$ are an eigenvalue/vector pair of A. Then

$$0 < \boldsymbol{x}^T A\boldsymbol{x} = \lambda\boldsymbol{x}^T\boldsymbol{x} \tag{41}$$

Since $\boldsymbol{x} \neq 0$ and $\boldsymbol{x}^T\boldsymbol{x}$ is positive (it's actually the squared 2-norm of $\boldsymbol{x}$), then $\lambda > 0$. Note that this part of the proves requires A be pd.

3. Let λ_i, λ_j be distinct eigenvalues of A, and $\boldsymbol{x}_i, \boldsymbol{x}_j$ the corresponding eigenvectors. Then

$$\boldsymbol{x}_i^T A \boldsymbol{x}_j = \lambda_j \boldsymbol{x}_i^T \boldsymbol{x}_j$$
$$\boldsymbol{x}_i^T A^T \boldsymbol{x}_j = (A\boldsymbol{x}_i)^T x_j = \lambda_i \boldsymbol{x}_i^T \boldsymbol{x}_j$$

   Since A is symmetric, these two string of equalities must be equal. We can subtract them to find that

$$(\lambda_i - \lambda_j)\boldsymbol{x}_i^T \boldsymbol{x}_j = 0 \tag{42}$$

   Since we assumed $\lambda_i \neq \lambda_j$, then it must be that $\boldsymbol{x}_i^T \boldsymbol{x}_j$. Therefore $x_i \perp x_j$. This proof again only relies on the symmetry of A.

4. This follows from the fact that the determinant of A is equal to the product of its eigenvalues.

5.

□

4.2 Banded Matrices

5 Simultaneous nonlinear equations

5.1 Analysis Preliminaries

Definition 15. *(Cauchy Sequence) A sequence $(\boldsymbol{x}^{(k)}) \subset \mathbb{R}^n$ is called a Cauchy sequence in $\mathbb{R}^n$ if for any $\epsilon > 0$ there exists a positive integer $k_0 = k_0(\epsilon)$ such that*

$$\|\boldsymbol{x}^{(k)} - \boldsymbol{x}^{(m)}\|_\infty < \epsilon \quad \forall k, m \geq k_0(\epsilon) \tag{43}$$

Remark 1. $\mathbb{R}^n$ is **complete** in the sense that every Cauchy sequence $(\boldsymbol{x}^{(k)})$ converges to some $\xi \in \mathbb{R}^n$.

Definition 16. *(Continuous function) Let $D \subset \mathbb{R}^n$ be nonempty and $f : D \to \mathbb{R}^n$. Given $\boldsymbol{\xi} \in D$, f is continuous at $\boldsymbol{\xi}$ if for every $\epsilon > 0$, there exists a $\delta = \delta(\epsilon) > 0$ such that for every $\boldsymbol{x} \in B(\boldsymbol{\xi}; \delta) \cap D$*

$$\|f(\boldsymbol{x}) - f(\boldsymbol{\xi})\|_\infty < \epsilon \tag{44}$$

Lemma 1. Let $D \subset \mathbb{R}^n$ be nonempty and $f : D \to \mathbb{R}^n$ be defined and continuous on D. If $(\boldsymbol{x}^{(k)}) \subset D$ converges in $\mathbb{R}^n$ to $\boldsymbol{\xi} \in D$, then $f(\boldsymbol{x}^{(k)})$ also converges to $f(\boldsymbol{\xi})$.

5.2 Simultaneous iteration

Definition 17. *(Lipschitz condition, constant, and contraction) Let D be a closed subset of $\mathbb{R}^n$ and $g : D \to D$. If there exists a positive constant L such that*

$$\|g(x) - g(y)\|_\infty \leq L\|x - y\|_\infty \tag{45}$$

for all $x, y \in D$, then g satisfies the Lipschitz condition on D in the ∞-norm. L is called the Lipschitz constant. If $L \in (0, 1)$, then g is called a contraction on D in the ∞-norm.

Observations about this definition:

- Any function g that satisfies the Lipschitz condition on D is continuous on D (to see this, set $\delta = \frac{\epsilon}{L}$).
- If g satisfies the Lipschitz condition on D in the ∞-norm, then it also does in the p-norm for $p \in [1, \infty)$ and vice-versa. However the size of L depends on the choice of norm.

Theorem 11. *(Contraction Mapping Theorem in $\mathbb{R}^n$) Suppose D is a closed subset of $\mathbb{R}^n$ and $g : \mathbb{R}^n \to \mathbb{R}^n$ is defined on D, and $g(D) \subset D$. Suppose further that g is a contraction on D in the ∞-norm. Then,*

1. *g has a unique fixed point $\boldsymbol{\xi} \in D$*
2. *The sequence $(\boldsymbol{x}^{(k)})$ defined by $\boldsymbol{x}^{(k+1)} = g(\boldsymbol{x}^k)$ converges to $\boldsymbol{\xi}$ for any starting value $x^{(0)} \in D$.*

Proof. □