

Eigenvalues and Eigenvectors

Definition 5.1: Suppose $A \in \mathbb{R}^{n \times n}$,

If $\lambda \in \mathbb{C}$ satisfies

$$Ax = \lambda x$$

and $x \neq 0$, then λ is called an eigenvalue of A . x is the associated eigenvector.

~~Proof~~:

Remark: Why do we care about eigenvalues and eigenvectors?

Consider a general dynamical system

$$\frac{dx}{dt} = Ax, \quad A \in \mathbb{R}^{n \times n}$$

$$x(0) = x_0.$$

A solution can be rewritten in the form:

$$x(t) = x(0) \underbrace{\exp(At)}.$$

Matrix exponential.

If we can "diagonalize" A , $A = Q D Q^{-1}$,

here Q is a matrix with eigenvectors in the columns, D is a diagonal matrix with the eigenvalues on the diagonal,

then the system of ODEs can be rewritten

$$\frac{dx}{dt} = Q D Q^{-1} x$$

$$\Leftrightarrow \frac{d(Q^{-1}x)}{dt} = D Q^{-1}x.$$

Defining $y = Q^{-1}x$, we obtain a new, decoupled set of ODEs:

$$\frac{dy}{dt} = D y, \quad \text{or:}$$

$$\frac{dy_i}{dt} = \lambda_i y_i,$$

and the eigenvalues tell us which components of y grow or decay.

Gerschgorin Thms

Definition 5.5 $A \in \mathbb{C}^{n \times n}$, $n \geq 2$, $A = (a_{ij})$

$D_i =$ Gerschgorin discs

$$= \{ z \in \mathbb{C} : |z - a_{ii}| \leq R_i \}$$

with $R_i = \sum_{\substack{j=1 \\ j \neq i}}^n |a_{ij}|$.

Thm 5.4 $A \in \mathbb{C}^{n \times n}$, $n \geq 2$. All of the eigenvalues of A are in $D = \bigcup_{i=1}^n D_i$

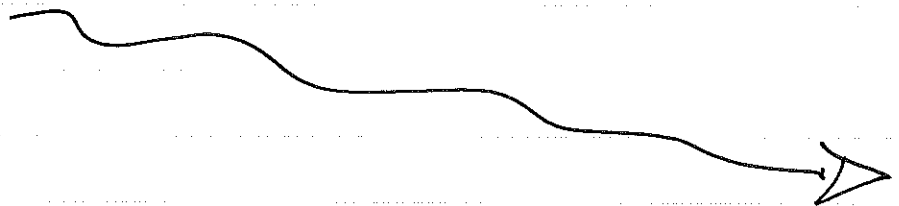
$D_i =$ Gerschgorin disc.

Pf. let (x, λ) be an eigenpair.
by definition

$$\sum_{j=1}^n a_{ij} x_j = \lambda x_i, \quad i=1, \dots, n.$$

Take x_k to be the component with largest absolute value: $|x_j| \leq |x_k|, j=1, \dots, n.$

Then



$$\begin{aligned} |\lambda - a_{kk}| |x_k| &= |\lambda x_k - a_{kk} x_k| \\ &= \left| \sum_{j=1}^n a_{kj} x_j - a_{kk} x_k \right| \\ &= \left| \sum_{\substack{j=1 \\ j \neq k}}^n a_{kj} x_j \right| \\ &\leq |x_k| R_k. \end{aligned}$$

This shows that $|\lambda - a_{kk}| \leq R_k$, i.e.
 λ is in D_k .

Thm 5.5: (Gerschgorin's 2nd theorem).

let $n \geq 2$.

let $1 \leq p \leq n-1$.

Suppose the Gerschgorin disks of $A \in \mathbb{C}^{n \times n}$ can be divided into two disjoint subsets $D^{(p)}$ and $D^{(q)}$.

p disks

$n-p$ disks.

Then $D^{(p)}$ contains exactly p eigenvalues
and $D^{(q)}$ contains exactly $n-p$ eigenvalues.

Proof: Next idea: define a matrix

$$B(\varepsilon) = (b_{ij}(\varepsilon)), \quad b_{ij}(\varepsilon) = \begin{cases} a_{ii} & i=j \\ \varepsilon a_{ij} & i \neq j \end{cases}$$

Note that $B(1) = A$. Also, note that the eigenvalues of $B(0)$ are the diagonal elements of A .

Now use continuity of the eigenvalues as a function of ε to finish the proof.

Fact: The eigenvalues of a matrix A are roots of the characteristic polynomial $p(\lambda) = \det(A - \lambda I)$.

Fact: There is a one-to-one correspondence between eigenvalue problems and root-finding problems.

i.e. If $p(z) = z^m + a_{m-1}z^{m-1} + \dots + a_1z + a_0$,

then the roots of p are actually the eigenvalues of the matrix

$$\begin{bmatrix} 0 & & & -a_0 \\ 1 & & & \\ & \ddots & & \\ & & 1 & 0 \\ & & & 1 & -a_{m-1} \end{bmatrix}$$

The above matrix is called the Companion matrix A_p .

Thm (Abel 1824).

For any $m \geq 5$, there is a polynomial $p(z)$ of degree m with rational coeff's that has a real root with the property that it cannot be written in any expression involving rational numbers, $+$, $-$, $*$, \div , and k^{th} roots.

Further issue: determining roots of a characteristic polynomial, or more generally any polynomial, is ill-conditioned.

Example: Consider the 2×2 identity matrix

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

writing down the characteristic polynomial,

we get $p(\lambda) = (\lambda - 1)^2 = \lambda^2 - 2\lambda + 1.$

If we perturb the constant coeff in this polynomial by 10^{-4} :

$$\tilde{p}(\lambda) = \lambda^2 - 2\lambda + 0.9999,$$

the roots of this perturbed poly are:

$$\tilde{p}(\lambda) = (\lambda - 0.99) (\lambda - 1.01),$$

i.e. they are perturbed by 10^{-2} from the original roots of $p(\lambda)$!!!

Power method for computing eigenvalues and eigenvectors.

Let's assume $A \in \mathbb{R}^{n \times n}$ is a real, symmetric matrix.

Definition: (Rayleigh Quotient).

$$r(x) = \frac{x^T A x}{x^T x}$$

Note that if x is an eigenvector of A , then $r(x) = \lambda$ is its corresponding eigenvalue.

Via taking derivatives, we can see that $\nabla r(x) = \frac{2}{x^T x} (Ax - r(x)x)$.

So, if x is an eigenvector of A , then $\nabla r(x) = 0$. And, if $\nabla r(x) = 0$ with $x \neq 0$, then x is an eigenvector of A , with eigenvalue $r(x)$.

Remark: let q_J be an eigenvector of A . we know that $\nabla r(q_J) = 0$.

By Taylor expansion, we have:

$$r(x) - r(q_J) = \nabla r(q_J)(x - q_J) + (x - q_J)^T \nabla^2 r(\xi)(x - q_J)$$

for some ξ on the line between x and q_J .

This shows that

$$|r(x) - r(q_J)| \leq C \|x - q_J\|^2,$$

since $\nabla r(q_J) = 0$.

The idea is if we have a good estimate for an ~~eigenvector~~ eigenvector, we can get a quadratically accurate estimate for the corresponding eigenvalue.



Power Method

let $v^{(0)}$ with $\|v^{(0)}\| = 1$ be some initial guess for an eigenvector of A . The power method, or power iteration, is defined as:

for $k=1, 2, \dots$

$$w = A v^{(k-1)}$$

$$v^{(k)} = w / \|w\|$$

$$\lambda^{(k)} = (v^{(k)})^T A v^{(k)}$$

apply A
normalize
Rayleigh
quotient.

The claim is that $\lambda^{(k)}$ converges to an eigenvalue of A and $v^{(k)}$ converges to the corresponding eigenvector, as $k \rightarrow \infty$. This iteration should converge to the largest eigenvalue in absolute value.

Thm: Suppose $|\lambda_1| > |\lambda_2| \geq \dots \geq |\lambda_m| \geq 0$

and $q_1^T v^{(0)} \neq 0$. Then the power iteration above creates iterates satisfying

$$\|v^{(k)} - (\pm q_1)\| = O\left(\left|\frac{\lambda_2}{\lambda_1}\right|^k\right), \quad |\lambda^{(k)} - \lambda_1| = O\left(\left|\frac{\lambda_2}{\lambda_1}\right|^{2k}\right).$$

Pf: Take the 1st iterate, $v^{(0)}$, and expand in the basis of eigenvectors of A :

$$v^{(0)} = a_1 q_1 + \dots + a_m q_m.$$

$w = Av^{(k-1)}$ is actually a multiple of $A^k v^{(0)}$, up to normalizing constants c_k , so:

$$\begin{aligned} w &= c_k A^k v^{(0)} \\ &= c_k (a_1 \lambda_1^k q_1 + a_2 \lambda_2^k q_2 + \dots + a_m \lambda_m^k q_m) \\ &= c_k a_1 \lambda_1^k \left(q_1 + \frac{a_2}{a_1} \left(\frac{\lambda_2}{\lambda_1} \right)^k q_2 + \dots + \frac{a_m}{a_1} \left(\frac{\lambda_m}{\lambda_1} \right)^k q_m \right) \\ &= c_k a_1 \lambda_1^k (q_1 + z_k). \end{aligned}$$

Now, we normalize:

$$v^{(k)} = \frac{w}{\|w\|} = \frac{(\pm) q_1 + z_k}{\|q_1 + z_k\|}$$

Why? Because we don't know the sign of c_k .

So:

$$\begin{aligned} v^{(k)} - (\pm) q_1 &= \frac{q_1 + z_k}{\|q_1 + z_k\|} - q_1 \frac{\|q_1 + z_k\|}{\|q_1 + z_k\|} \\ &= \frac{(1 - \|q_1 + z_k\|) q_1}{\|q_1 + z_k\|} + \frac{z_k}{\|q_1 + z_k\|} \end{aligned}$$

$$\text{So: } \|v^{(k)} - q_1\|$$

$$\leq \frac{|1 - \|q_1 + z_k\|| \|q_1\|}{\|q_1 + z_k\|} + \frac{\|z_k\|}{\|q_1 + z_k\|}$$

$$= \left(|1 - \|q_1 + z_k\|| + \|z_k\| \right) \frac{1}{\|q_1 + z_k\|}$$

$$= \left(|\|q_1\| - \|q_1 + z_k\|| + \|z_k\| \right) \frac{1}{\|q_1 + z_k\|}$$

$$\leq \frac{2 \|z_k\|}{\|q_1 + z_k\|}$$

Back
half of
 Δ -inequality

$$\text{i.e. } \|v^{(k)} - q_1\| \rightarrow 0 \text{ as } \|z_k\| \rightarrow 0.$$

Note that $\|z_k\| \rightarrow 0$ with a rate that depends on the ratio $\left(\frac{\lambda_2}{\lambda_1}\right)^k$.

The rate of convergence for the eigenvalues ~~approximations~~ $\lambda^{(k)}$ is given by the properties of the Rayleigh quotient.

Inverse Iteration:

What about finding other eigenvalues and eigenvectors?

Idea: "Shift" the matrix A so that we change the dominant eigenvalue:

Take $\mu \in \mathbb{R}$, μ not an eigenvalue of A .

Let $\{\lambda_j\}$ be the eigenvalues of A .

Then $\{\lambda_j - \mu\}$ are the eigenvalues of $(A - \mu I)$.

and $\{(\lambda_j - \mu)^{-1}\}$ are the eigenvalues of $(A - \mu I)^{-1}$.

If $\mu \approx \lambda_j$, then $(\lambda_j - \mu)^{-1}$ is really big, and probably the largest eigenvalue of $(A - \mu I)^{-1}$ in magnitude.

→ Apply power method to $(A - \mu I)^{-1}$.

Inverse Iteration Algorithm:

$$v^{(0)}, \quad \|v^{(0)}\| = 1.$$

for $k = 1, 2, \dots$

Solve $(A - \mu I)w = v^{(k-1)}$ for w .

$$v^{(k)} = w / \|w\|$$

$$\lambda^{(k)} = v^{(k)T} A v^{(k)}.$$
