Characteristic Polynomial

Preleminary Results. Let $A = (a_{ij})$ be an $n \times n$ matrix. If $Au = \lambda u$, then λ and u are called the *eigenvalue* and *eigenvector* of A, respectively. The eigenvalues of A are the roots of the *characteristic polynomial*

$$K_A(\lambda) = \det (\lambda I_n - A).$$

The eigenvectors are the solutions to the Homogeneous system

$$(\lambda I_n - A) X = \theta.$$

Note that $K_A(\lambda)$ is a monic polynomial (i.e., the leading coefficient is one).

Cayley-Hamilton Theorem. If $K_A(\lambda) = \lambda^n + p_1\lambda^{n-1} + \cdots + p_{n-1}\lambda + p_n$ is the characteristic polynomial of the $n \times n$ matrix A, then

$$K_A(A) = A^n + p_1 A^{n-1} + \dots + p_{n-1} A + p_n I_n = Z_n,$$

where Z_n is the $n \times n$ zero matrix.

Corollary. Let $K_A(\lambda) = \lambda^n + p_1 \lambda^{n-1} + \dots + p_{n-1} \lambda + p_n$ be the characteristic polynomial of the $n \times n$ invertible matrix A. Then

$$A^{-1} = \frac{1}{-p_n} \left[A^{n-1} + p_1 A^{n-2} + \dots + p_{n-2} A + p_{n-1} I_n \right].$$

Proof. According to the Cayley Hamilton's theorem we have

$$A \left[A^{n-1} + p_1 A^{n-2} + \dots + p_{n-1} I_n \right] = -p_n I_n$$

Since A is nonsingular, $p_n = (-1)^n \det(A) \neq 0$; thus the result follows.

Newton's Identity. Let $\lambda_1, \lambda_2, \ldots, \lambda_n$ be the roots of the polynomial

$$P(\lambda) = \lambda^n + c_1 \lambda^{n-1} + c_2 \lambda^{n-2} + \dots + c_{n-1} \lambda + c_n.$$

If $s_k = \lambda_1^k + \lambda_2^k + \dots + \lambda_n^k$, then

$$c_k = -\frac{1}{k} \left(s_k + s_{k-1}c_1 + s_{k-2}c_2 + \dots + s_2c_{k-2}c_1 + s_1c_{k-1} \right).$$

Proof. From

$$P(\lambda) = (\lambda - \lambda_1)(\lambda - \lambda_2)\dots(\lambda - \lambda_{n-1})(\lambda - \lambda_n)$$

and the use of logarithmic differentiation, we obtain

$$\frac{P'(\lambda)}{P(\lambda)} = \frac{n\lambda^{n-1} + (n-1)c_1\lambda^{n-2} + \dots + 2c_{n-2}\lambda + c_{n-1}}{\lambda^n + c_1\lambda^{n-1} + c_2\lambda^{n-2} + \dots + c_{n-1}\lambda + c_n} = \sum_{i=1}^n \frac{1}{(\lambda - \lambda_i)} \ .$$

By using the geometric series for $\frac{1}{(\lambda - \lambda_i)}$ and choosing $|\lambda| > \max_{1 \le i \le n} |\lambda_i|$, we obtain

$$\sum_{i=1}^{n} \frac{1}{(\lambda - \lambda_i)} = \frac{n}{\lambda} + \frac{s_1}{\lambda^2} + \frac{s_2}{\lambda^3} + \cdots$$

Hence

$$n\lambda^{n-1} + (n-1)c_1\lambda^{n-2} + \dots + c_{n-1} = \left(\lambda^n + c_1\lambda^{n-1} + c_2\lambda^{n-2} + \dots + c_n\right)\left(\frac{n}{\lambda} + \frac{s_1}{\lambda^2} + \frac{s_2}{\lambda^3} + \dots\right).$$

By equating both sides of the above equality we may obtain the Newton's identities.

***** The Method of Direct Expansion. The characteristic polynomial of an $n \times n$ matrix $A = (a_{ij})$ is defined as:

$$K_{A}(\lambda) = \det(\lambda I_{n} - A) = \begin{vmatrix} \lambda - a_{11} & -a_{12} & \dots & -a_{1n} \\ -a_{21} & \lambda - a_{22} & \dots & -a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ -a_{n1} & -a_{n2} & \dots & \lambda - a_{nn} \end{vmatrix} = \lambda^{n} - \sigma_{1}\lambda^{n-1} + \sigma_{2}\lambda^{n-2} - \dots + (-1)^{n}\sigma_{n},$$

where

$$\sigma_1 = \sum_{i=1}^n a_{ii} = trace(A)$$

is the sum of all first-order diagonal minors of A,

$$\sigma_2 = \sum_{i < j} \begin{vmatrix} a_{ii} & a_{ij} \\ a_{ji} & a_{jj} \end{vmatrix}$$

is the sum of all second-order diagonal minors of A,

$$\sigma_3 = \sum_{i < j < k} \begin{vmatrix} a_{ii} & a_{ij} & a_{ik} \\ a_{ji} & a_{jj} & a_{jk} \\ a_{ki} & a_{kj} & a_{kk} \end{vmatrix}$$

is the sum of all third-order diagonal minors of A, and so forth. Finally,

$$\sigma_n = det(A)$$

There are $\binom{n}{k}$ diagonal minors of order k in A. From this we find that the direct computation of the coefficients of the characteristic polynomial of an $n \times n$ matrix is equivalent to computing

$$\binom{n}{1} + \binom{n}{2} + \dots \binom{n}{n} = 2^n - 1$$

determinants of various orders, which, generally speaking, is a major task. This has given rise to special methods for expanding characteristic polynomial. We shall explain some of these methods.

Example. Compute the characteristic polynomial of
$$A = \begin{pmatrix} 1 & 2 & 3 \\ 2 & 1 & -4 \\ 1 & 0 & 2 \end{pmatrix}$$
.

We have:

$$\sigma_1 = 1 + 1 + 2 = 4, \quad \sigma_2 = \begin{vmatrix} 1 & 2 \\ 2 & 1 \end{vmatrix} + \begin{vmatrix} 1 & -4 \\ 0 & 2 \end{vmatrix} + \begin{vmatrix} 1 & 3 \\ 1 & 2 \end{vmatrix} = (-3) + (2) + (-1) = -2,$$

and
$$\sigma_3 = \det(A) = \begin{vmatrix} 1 & 2 & 3 \\ 2 & 1 & -4 \\ 1 & 0 & 2 \end{vmatrix} = -17.$$

Thus

$$K_A(\lambda) = \det(\lambda I_3 - A) = \lambda^3 - \sigma_1 \lambda^2 + \sigma_2 \lambda - \sigma_3 = \lambda^3 - 4\lambda - 2\lambda + 17\lambda^2$$

Leverrier's Algorithm. This method allows us to find the characteristic polynomial of any $n \times n$ matrix A using the trace of the matrix A^k , where $k = 1, 2, \dots n$. Let

$$\sigma(A) = \{\lambda_1, \lambda_2, \cdots, \lambda_n\}$$

be the set of all eigenvalues of A which is also called the *spectrum* of A. Note that

$$s_k = trace(A^k) = \sum_{i=1}^n \lambda_i^k$$
, for all $k = 1, 2, \cdots, n$.

Let

$$K_A(\lambda) = \det(\lambda I_n - A) = \lambda^n + p_1 \lambda^{n-1} + \dots + p_{n-1} \lambda + p_n$$

be the characteristic polynomial of the matrix A, then for $k \leq n$, the Newton's identities hold true:

$$p_k = -\frac{1}{k} \left[s_k + p_1 s_{k-1} + \dots + p_{k-1} s_1 \right] \quad (k = 1, 2, \dots, n)$$

Example. Let
$$A = \begin{pmatrix} 1 & 2 & 1 & -1 \\ 1 & 0 & 2 & 1 \\ 2 & 1 & -1 & 3 \\ 4 & -5 & 0 & 4 \end{pmatrix}$$
. Then

$$A^{2} = \begin{pmatrix} 1 & 8 & 4 & 0 \\ 9 & -1 & -1 & 9 \\ 13 & -12 & 5 & 8 \\ 15 & -12 & -6 & 7 \end{pmatrix} \quad A^{3} = \begin{pmatrix} 17 & 6 & 13 & 19 \\ 42 & -28 & 8 & 23 \\ 43 & -9 & -16 & 22 \\ 19 & -11 & -3 & -17 \end{pmatrix} \quad A^{4} = \begin{pmatrix} 125 & -48 & 16 & 104 \\ 122 & -23 & -22 & 46 \\ 90 & -40 & 41 & -12 \\ -66 & 120 & 0 & -107 \end{pmatrix}.$$

So $s_1 = 4$, $s_2 = 12$, $s_3 = -44$, and $s_4 = 36$. Hence

$$\begin{cases} p_1 = -s_1 = -4, \\ p_2 = -\frac{1}{2}(s_2 + p_1 s_1) = -\frac{1}{2}(12 + (-4)4) = 2, \\ p_3 = -\frac{1}{3}(s_3 + p_1 s_2 + p_2 s_1) = -\frac{1}{3}(-44 + (-4)12 + 2(4)) = 28, \\ p_4 = -\frac{1}{4}(s_4 + p_1 s_3 + p_2 s_2 + p_3 s_1) = -\frac{1}{4}(36 + (-4)(-44) + 2(12) + 28(4)) = -87. \end{cases}$$

Therefore

$$K_A(\lambda) = \lambda^4 - 4\lambda^3 + 2\lambda^2 + 28\lambda - 87$$

and

$$A^{-1} = \frac{1}{87} \left[A^3 - 4A^2 + 2A + 28I_4 \right] =$$

$$\frac{1}{87} \begin{bmatrix} \begin{pmatrix} 17 & 6 & 13 & 19 \\ 42 & -28 & 8 & 23 \\ 43 & -9 & -16 & 22 \\ 19 & -11 & -3 & -17 \end{bmatrix} - 4 \begin{pmatrix} 1 & 8 & 4 & 0 \\ 9 & -1 & -1 & 9 \\ 13 & -12 & 5 & 8 \\ 15 & -12 & -6 & 7 \end{pmatrix} + 2 \begin{pmatrix} 1 & 2 & 1 & -1 \\ 1 & 0 & 2 & 1 \\ 2 & 1 & -1 & 3 \\ 4 & -5 & 0 & 4 \end{pmatrix} + 28 \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \end{bmatrix}$$

$$A^{-1} = \frac{1}{87} \begin{pmatrix} 43 & -22 & -1 & 17\\ 8 & 4 & 16 & -11\\ -5 & 41 & -10 & -4\\ -33 & 27 & 21 & -9 \end{pmatrix}.$$

California State University, East Bay

Page 3

The Method of Souriau

The Method of Souriau (or Fadeev and Frame). This is an elegant modification of the Leverrier's method.

Let A be an $n \times n$ matrix, then define

$$\begin{array}{lll} A_{1} = A, & q_{1} = -trace(A_{1}), & B_{1} = A_{1} + q_{1}I_{n} \\ A_{2} = AB_{1}, & q_{2} = -\frac{1}{2}trace(A_{2}), & B_{2} = A_{2} + q_{2}I_{n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ A_{n} = AB_{n-1}, & q_{n} = -\frac{1}{n}trace(A_{n}), & B_{n} = A_{n} + q_{n}I_{n} \end{array}$$

Theorem. $B_n = Z_n$, and

$$K_A(\lambda) = \det(\lambda I_n - A) = \lambda^n + q_1 \lambda^{n-1} + \dots + q_{n-1} \lambda + q_n \,.$$

If A is nonsingular, then

$$A^{-1} = -\frac{1}{q_n} B_{n-1} \,.$$

Proof. Suppose the characteristic polynomial of A is

$$K_A(\lambda) = \det(\lambda I_n - A) = \lambda^n + p_1 \lambda^{n-1} + \dots + p_{n-1} \lambda + p_n ,$$

where $p'_k s$ are defined in the Leverrier's method.

Clearly $p_1 = -trace(A) = -trace(A_1) = q_1$, and now suppose that we have proved that

$$q_1 = p_1, q_2 = p_2, \ldots, q_{k-1} = p_{k-1}.$$

Then by the hypothesis we have

$$A_{k} = AB_{k-1} = A(A_{k-1} + q_{k-1}I_{n}) = AA_{k-1} + q_{k-1}A$$

= $A[A(A_{k-2} + q_{k-2}I_{n})] + q_{k-1}A$
= $A^{2}A_{k-1} + q_{k-2}A^{2} + q_{k-1}A$
= $\cdots \cdots \cdots \cdots \cdots \cdots \cdots \cdots$
= $A^{k} + q_{1}A^{k-1} + \cdots + q_{k-1}A$.

Let $s_i = trace(A^i)$ (i = 1, 2, ..., k), then by Newton's identities

$$-kq_{k} = trace(A_{k}) = trace(A^{k}) + q_{1} \ trace(A^{k-1}) + \dots + q_{k-1} \ trace(A)$$
$$= s_{k} + q_{1}s_{k-1} + \dots + q_{k-1}s_{1}$$
$$= s_{k} + p_{1}s_{k-1} + \dots + p_{k-1}s_{1}$$
$$= -kp_{k}.$$

showing that $p_k = q_k$. Hence this relation holds for all k.

By the Cayley-Hamilton theorem,

$$B_n = A^n + q_1 A^{n-1} + \dots + q_{n-1} A + q_n I_n = Z_n$$

and so

$$B_n = A_n + q_n I_n = Z_n;$$
 $A_n = AB_{n-1} = -q_n I_n.$

If A is nonsingular, then $det(A) = (-1)^n K_A(0) = (-1)^n q_n \neq 0$, and thus

ŀ

$$A^{-1} = -\frac{1}{q_n} B_{n-1} \,.$$

Example. Find the characteristic polynomial and if possible the inverse of the matrix

$$A = \begin{pmatrix} 1 & 2 & 1 & -1 \\ 1 & 0 & 2 & 1 \\ 2 & 1 & -1 & 3 \\ 4 & -5 & 0 & 4 \end{pmatrix}.$$

For k = 1, 2, 3, 4, compute

$$A_k = AB_{k-1} \qquad q_k = \frac{-1}{k} trace(A_k), \qquad B_k = A_k + q_k I_4.$$

Therefore the characteristic polynomial of A is:

$$K_A(\lambda) = \lambda^4 - 4\lambda^3 + 2\lambda^2 + 28\lambda - 87.$$

Note that A_4 is a diagonal matrix, so we only need to multiply the first row of A by the first column of B_3 to obtain 87. Since $q_4 = -87$, the matrix A has an inverse.

$$A^{-1} = \frac{-1}{q_4} B_3 = \frac{1}{87} \begin{pmatrix} 43 & -22 & -1 & 17\\ 8 & 4 & 16 & -11\\ -5 & 41 & -10 & -4\\ -33 & 27 & 21 & -9 \end{pmatrix} .$$

Matlab Program

 $\begin{array}{l} A=input('Enter\ a\ square\ matrix\ :\ ')\\ m=size(A);\ n=m(1);\ q=zeros(1,n);\ B=A;\ AB=A;\ In=eye(n);\\ for\ k=1:n-1,\ q(k)=-(1/k)*trace(AB)B=AB+q(k)*In;\ AB=A*B;\ end\\ C=B;\ q(n)=-(1/n)*trace(AB);\ Q=[1\ q];\\ disp('The\ Characteristic\ polynomial\ looks\ like\ :\ ')\\ disp('The\ Characteristic\ polynomial\ looks\ like\ :\ ')\\ disp('The\ coefficients\ list\ c(k)\ is\ :\ '),\ disp('\ '),\\ disp(Q),\ disp('\ ')\\ if\ q(n)==0,\ disp('The\ matrix\ is\ singular\ ');\\ else,\ disp('The\ matrix\ has\ an\ inverse.\ '),\ disp('\ ')\\ C=-(1/q(n))*B;\\ disp('The\ inverse\ of\ A\ is\ :\ '),disp('\ '),\\ disp(C)\\ end \end{array}$

California State University, East Bay

u cocjjucienus i ag

<u>*</u> <u>The Method of Undetermined Coefficients</u>. If one has to expand large numbers of characteristic polynomials of the same order, then the method of undetermined coefficients may be used to produce characteristic polynomials of those matrices.

Let A be an $n \times n$ matrix and

$$K_A(\lambda) = \det(\lambda I_n - A) = \lambda^n + p_1 \lambda^{n-1} + \dots + p_{n-1} \lambda + p_n$$

be its characteristic polynomial. In order to find the coefficients p'_i s of $K_A(\lambda)$ we evaluate

$$D_j = K_A(j) = \det(jI_n - A)$$
 $j = 0, 1, 2, \dots, n-1$

and obtain the following system of linear equations:

$$\begin{cases} p_n = D_0 \\ 1^n + p_1 \cdot 1^{n-1} + \dots + p_n = D_1 \\ 2^n + p_1 \cdot 2^{n-1} + \dots + p_n = D_2 \\ \dots \\ (n-1)^n + p_1 \cdot (n-1)^{n-1} + \dots + p_n = D_{n-1} \end{cases}$$

Which can be changed into:

$$S_{n-1}P = \begin{bmatrix} 1^{n-1} & 1^{n-2} & \dots & 1\\ 2^{n-1} & 2^{n-2} & \dots & 2\\ \vdots & \vdots & \ddots & \vdots\\ (n-1)^{n-1} & (n-1)^{n-2} & \dots & n-1 \end{bmatrix} \begin{bmatrix} p_1\\ p_2\\ \vdots\\ p_{n-1} \end{bmatrix} = \begin{bmatrix} D_1 - D_0 - 1^n\\ D_2 - D_0 - 2^n\\ \vdots & \vdots & \vdots\\ D_{n-1} - D_0 - (n-1)^n \end{bmatrix} = D$$

The system may be solved as follows:

 $P = S_n^{-1} D.$

Since the $(n-1) \times (n-1)$ matrix S_n depends only on the order of A, we may store R_n , the inverse of S_{n-1} beforehand and use it to find the coefficients of characteristic polynomial of various $n \times n$ matrices.

Examples. Compute the characteristic polynomials of the 4×4 matrices

$$A = \begin{pmatrix} 1 & 3 & 0 & 4 \\ 2 & -3 & 1 & 3 \\ 1 & 2 & 1 & 2 \\ -1 & 3 & 2 & 1 \end{pmatrix} \text{ and } B = \begin{pmatrix} 1 & 2 & 1 & -1 \\ 1 & 0 & 2 & 1 \\ 2 & 1 & -1 & 3 \\ 4 & -5 & 0 & 4 \end{pmatrix}.$$

First we find

$$S = \begin{pmatrix} 1 & 1 & 1 \\ 8 & 4 & 2 \\ 27 & 9 & 3 \end{pmatrix} \quad \text{and} \quad R = S^{-1} = -\frac{1}{12} \begin{pmatrix} -6 & 6 & -2 \\ 30 & -24 & 6 \\ -36 & 18 & -4 \end{pmatrix}.$$

Then for the matrix A we obtain

$$D_0 = \det(-A) = -48, \quad D_1 = \det(I_4 - A) = -72,$$

$$D_2 = \det(2I_4 - A) = -128 \quad \text{and} \quad D_3 = \det(3I_4 - A) = -180$$

$$D = \begin{pmatrix} D_1 - D_0 - 1^4 \\ D_2 - D_0 - 2^4 \\ D_3 - D_0 - 3^4 \end{pmatrix} = \begin{pmatrix} -25 \\ -96 \\ -213 \end{pmatrix}.$$

The Method of Undetermined Coefficients

Hence

$$P = \begin{pmatrix} p_1 \\ p_2 \\ p_3 \end{pmatrix} = -\frac{1}{12} \begin{pmatrix} -6 & 6 & -2 \\ 30 & -24 & 6 \\ -36 & 18 & -4 \end{pmatrix} \begin{pmatrix} -25 \\ -96 \\ -213 \end{pmatrix} = \begin{pmatrix} 0 \\ -23 \\ -2 \end{pmatrix}.$$

Thus

$$K_A(\lambda) = \lambda^4 - 23\lambda^2 - 2\lambda - 48$$

For the matrix B we have

$$D_0 = \det(-B) = -87, \quad D_1 = \det(I_4 - B) = -60,$$

 $D_2 = \det(2I_4 - B) = -39 \text{ and } D_3 = \det(3I_4 - B) = -12$

$$D = \begin{pmatrix} D_1 - D_0 - 1^4 \\ D_2 - D_0 - 2^4 \\ D_3 - D_0 - 3^4 \end{pmatrix} = \begin{pmatrix} 26 \\ 32 \\ -6 \end{pmatrix}.$$

Hence

$$P = \begin{pmatrix} p_1 \\ p_2 \\ p_3 \end{pmatrix} = -\frac{1}{12} \begin{pmatrix} -6 & 6 & -2 \\ 30 & -24 & 6 \\ -36 & 18 & -4 \end{pmatrix} \begin{pmatrix} 26 \\ 32 \\ -6 \end{pmatrix} = \begin{pmatrix} -4 \\ 2 \\ 28 \end{pmatrix}.$$

Thus

$$K_B(\lambda) = \lambda^4 - 4\lambda^3 + 2\lambda^2 + 28\lambda - 87$$

Matlab Program

N = input('Enter the size of your square matrix : ');n = N - 1; In = eye(N); S = zeros(n); R = zeros(n); D = zeros(1, n); DSP1 = [' For any ', int2str(N), '-square matrix, you need S = '];DSP2 = ['Do you want to try with another', int2str(N), '-square matrix? (Yes = 1/No = 0)'];%DEFINING S for i = 1 : n, for j = 1 : n, $S(i, j) = i \land (N - j)$; end; end; $disp(' \ '), \ disp(DSP1), \ disp(' \ '), \ disp(S),$ R = inv(S);ok = 1;while ok == 1; $A = input(['Enterna', int2str(N), 'x', int2str(N), 'matrix A : '); \quad disp('')$ D0 = det(A);for k = 1 : n; D(k) = det(k * In - A); end; for i = 1 : n; $DD(i) = D(i) - D0 - i \wedge N$; end; P = R * DD';disp('The Characteristic polynomial looks like : ') $disp('K_A(x) = x \wedge n + p(1)x \wedge (n-1) + ... + p(n-1)x + p(n)'), \ disp(''),$ $disp('The \ coefficients \ list \ p(k) \ is \ : \ '), \ disp('\ '),$ disp([1 P' D0]), disp(''), $disp(DSP2), \ disp(' \ '),$ ok = input(DSP2);end

4 The Method of Danilevsky. Consider an $n \times n$ matrix A and let

$$K_A(\lambda) = det(\lambda I_n - A) = \lambda^n + p_1 \lambda^{n-1} + \dots + p_{n-1} \lambda + p_n$$

be its characteristic polynomial. Then the companion matrix of $K_A(\lambda)$

	$(-p_1)$	$-p_{2}$	$-p_3$		$-p_{n-1}$	$-p_n $
F[A] =	1	0			0	0
	0	1			0	0
	:	÷	·	·		:
	0	0		1	0	0
	0	0	0		1	0 /

is similar to A and is called the *Frobenius form* of A.

The method of Danilevsky (1937) applies the Gauss-Jordan method to obtain the Frobenius form of an $n \times n$ matrix. According to this method the transition from the matrix A to F[A] is done by means of n-1 similarity transformations which successively transform the rows of A, beginning with the last, into corresponding rows of F[A].

Let us illustrate the beginning of the process. Our purpose is to carry the *nth* row of

	(a_{11})	a_{12}	a_{13}		$a_{1,n-1} \\ a_{2,n-1}$	a_{1n}
A =	a_{21}	a_{22}	a_{23}		$a_{2,n-1}$	a_{2n}
	a_{31}	a_{32}	a_{33}		$a_{3,n-1}$	a_{3n}
	÷	:	÷	·	$a_{3,n-1}$	÷
	$\binom{\ldots}{a_{n1}}$	a_{n2}	a_{n3}	· · · · · · · ·	$a_{n,n-1}$	$\begin{pmatrix} & \cdots & \\ & a_{nn} \end{pmatrix}$

into the row $(0 \ 0 \ \dots \ 1 \ 0)$. Assuming that $a_{n,n-1} \neq 0$, we replace the (n-1)th row of the $n \times n$ identity matrix with the *nth* row of A and obtained the matrix

$$U_{n-1} = \begin{pmatrix} 1 & 0 & 0 & \dots & 0 & 0 \\ 0 & 1 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \dots & \vdots & \vdots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ a_{n1} & a_{n2} & a_{n3} & \dots & a_{n,n-1} & a_{nn} \\ 0 & 0 & 0 & \dots & 0 & 1 \end{pmatrix}$$

The inverse of U_{n-1} is

$$V_{n-1} = \begin{pmatrix} 1 & 0 & 0 & \dots & 0 & 0 \\ 0 & 1 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \dots & \vdots & \vdots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ v_{n-1,1} & v_{n-1,2} & v_{n-1,3} & \dots & v_{n-1,n-1} & v_{n-1,n} \\ 0 & 0 & 0 & \dots & 0 & 1 \end{pmatrix}$$

where

$$v_{n-1,i} = -\frac{a_{ni}}{a_{n,n-1}} \qquad \text{for} \quad i \neq n-1$$

and $v_{n-1,n-1} = -\frac{1}{a_{n,n-1}}$.

California State University, East Bay

Page 8

Multiplying the right side of A by V_{n-1} , we obtain

$$AV_{n-1} = B = \begin{pmatrix} b_{11} & b_{12} & b_{13} & \dots & b_{1,n-1} & b_{1n} \\ b_{21} & b_{22} & b_{23} & \dots & b_{2,n-1} & b_{2n} \\ \vdots & \vdots & \ddots & \dots & \vdots & \vdots \\ \dots & \dots & \dots & \dots & \dots & \dots \\ b_{n-1,1} & b_{n-1,2} & b_{n-1,3} & \dots & b_{n-1,n-1} & b_{n-1,n-1} \\ 0 & 0 & 0 & \dots & 1 & 0 \end{pmatrix}$$

However the matrix $B = AM_{n-1}$ is not similar to A. To have a similarity transformation, it is necessary to multiply the left side of B by $U_{n-1} = V_{n-1}^{-1}$. Let $C = U_{n-1}AV_{n-1}$, then C is similar to A and is of the form

	$ \begin{pmatrix} c_{11} \\ b_{21} \end{pmatrix} $	$c_{12} \\ b_{22}$		 	$c_{1,n-1} \\ b_{2,n-1}$	$\begin{pmatrix} c_{1n} \\ b_{2n} \end{pmatrix}$
C =	÷	•	·•.		:	:
	$\begin{pmatrix} \dots \\ c_{n-1,1} \\ 0 \end{pmatrix}$	$\begin{array}{c} c_{n-1,2} \\ 0 \end{array}$	$\begin{array}{c} c_{n-1,3} \\ 0 \end{array}$	· · · · · · · · · · · · · · · · · · ·	$c_{n-1,n-1}$	$\begin{pmatrix} c_{n-1,n-1} \\ 0 \end{pmatrix}$

Now, if $c_{n-1,n-1} \neq 0$, then similar operations are performed on matrix C by taking its (n-2)th row as the principal one. We then obtain the matrix

$$D = U_{n-2}CV_{n-2} = U_{n-2}U_{n-1}AV_{n-1}V_{n-2}$$

with two reduced rows. We continue the same way until we finally obtain the Frobenius form

$$F[A] = U_1 U_2 \cdots U_{n-2} U_{n-1} A V_{n-1} V_{n-2} \cdots V_2 V_1$$

if, of course, all the n-1 intermediate transformations are possible.

Exceptional case in the Danilevsky method. Suppose that in the transformation of the matrix A into its Frobenius form F[A] we arrived, after a few steps, at a matrix of the form

	$\begin{pmatrix} r_{11} \\ r_{21} \end{pmatrix}$	$r_{12} \\ r_{22}$	· · · · · · ·	$r_{1k} \\ r_{2k}$	 	$r_{1,n-1} \\ r_{2,n-1}$	$\begin{pmatrix} r_{1n} \\ r_{2n} \end{pmatrix}$
R =	$r_{k1} \\ 0$	r_{k2} 0	· · · · · · · · · · · · · · · · · · ·	r_{kk} 1	· · · · · · · · · · · · · · · · · · ·	$\begin{array}{c} \cdots \\ r_{k,n-1} \\ 0 \end{array}$	$\begin{array}{c} \dots \\ r_{kn} \\ 0 \end{array}$
	0	0		0	•••	0	0
	$\begin{pmatrix} \dots \\ 0 \end{pmatrix}$	0	· · · · · · · ·	0	· · · · · · · · · · · · · · · · · · ·	 1	$\begin{pmatrix} & & & \\ & & & \\ & & & \\ & & & \\ & & & & & \\ & & & & \\ & & & & \\ & & & & & \\ & & & & & \\ & & & & \\ & & & & \\ & & & & & \\ & & & & & \\ & & & & & $

and it was found that $r_{k,k-1} = 0$ or $|r_{k,k-1}|$ is very small. It is then possible to continue the transformation by the Danilevsky method.

Two cases are possible here.

Case 1. Suppose for some j = 1, 2, ..., k - 2, $r_{kj} \neq 0$. Then by permuting the *jth* row and (k-1)th row and the *jth* column and (k-1)th column of R we obtain a matrix $R' = (r'_{ij})$ similar to R with $r'_{k,k-1} \neq 0$.

Case 2. Suppose now that $r_{kj} = 0$ for all j = 1, 2, ..., k - 2. Then R is in the form

$$R = \begin{bmatrix} R_1 & R_2 \\ 0 & R_3 \end{bmatrix} = \begin{pmatrix} r_{11} & r_{12} & \dots & r_{1,k-1} & r_{1,k} & r_{1,k+1} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2,k-1} & r_{2,k} & r_{2,k+1} & \dots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ r_{k-1,1} & r_{k-1,2} & \dots & r_{k-1,k-1} & r_{k-1,k} & r_{k-1,k+1} & \dots & r_{k-1,n} \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & 0 & 1 & \dots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 0 & 0 & \dots & 1 & 0 \end{pmatrix}$$

In this case the characteristic polynomial of R breaks up into two determinants:

$$\det(\lambda I_n - R) = \det(\lambda I_{k-1} - R_1) \det(\lambda I_{n-k+1} - R_3).$$

Here, the matrix R_3 is already reduced to the Frobenius form. It remains to apply the Danilevsky's method to the matrix R_1 .

Note. Since $U_k A_{k-1}$ only changes the kth row of A_{k-1} , it is more efficient to multiply first A_{k-1} by its (k+1)th row and then multiply on the right side the resulting matrix by V_k .

The next result shows that once we transform A into its Frobenius form ; we may obtain the eigenvectors with the help of the matrices V'_is .

Theorem. Let A be an $n \times n$ matrix and let F[A] be its Frobenius form. If λ is an eigenvalue of A, then

$$v = \begin{pmatrix} \lambda^{n-1} \\ \lambda^{n-2} \\ \vdots \\ \lambda \\ 1 \end{pmatrix} \quad \text{and} \quad w = V_{n-1}V_{n-2}\cdots V_2V_1v$$

are the eigenvectors of F[A] and A respectively.

Proof. Since

$$\det(\lambda I_n - A) = \det(\lambda I_n - F[A]) = \lambda^n + p_1 \lambda^{n-1} + \dots + p_{n-1} \lambda + p_n,$$

we have

$$(\lambda I_n - F[A])v = \begin{pmatrix} \lambda - p_1 & -p_2 & -p_3 & \dots & -p_{n-1} & -p_n \\ 1 & \lambda & 0 & \dots & 0 & 0 \\ \lambda & 1 & 0 & \dots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & 1 & \lambda \end{pmatrix} \begin{pmatrix} \lambda^{n-1} \\ \lambda^{n-2} \\ \lambda^{n-3} \\ \vdots \\ \lambda \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{pmatrix}.$$

Since $F[A] = V_1^{-1}V_2^{-1}\cdots V_{n-2}^{-1}V_{n-1}^{-1}AV_{n-1}V_{n-2}\cdots V_2V_1$ and $F[A]v = \lambda v$, we conclude that

$$\lambda w = V_{n-2} \cdots V_2 V_1(\lambda v) = (V_{n-2} \cdots V_2 V_1) F[A]v = A (V_{n-1} V_{n-2} \cdots V_2 V_1 v) = Aw$$

Note. For expanding characteristic polynomials of matrices of order higher than fifth, the method of Danilevsky requires less multiplications and additions than other methods.

Example. Reduce the matrix

$$A = \begin{pmatrix} 1 & 1 & 3 & 4 \\ 2 & 0 & 2 & 1 \\ 1 & 0 & 1 & 2 \\ 0 & 0 & -1 & -1 \end{pmatrix}$$

to its Frobenius form.

The matrix $B = A_3 = U_3 A V_3$ is as follows:

$$B = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & -1 & -1 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 1 & 3 & 4 \\ 2 & 0 & 2 & 1 \\ 1 & 0 & 1 & 2 \\ 0 & 0 & -1 & -1 \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & -1 & -1 \\ 0 & 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} 1 & 1 & -3 & 1 \\ 2 & 0 & -2 & -1 \\ -1 & 0 & 0 & -1 \\ 0 & 0 & 1 & 0 \end{pmatrix}.$$

Since $b_{32} = 0$, we need the permutation matrix $J = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix}$; thus

$$C = JBJ = \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 1 & 1 & -3 & 1 \\ 2 & 0 & -2 & -1 \\ 1 & 0 & -1 & 1 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} 0 & 2 & -2 & -1 \\ 1 & 1 & -3 & 1 \\ 0 & -1 & 0 & -1 \\ 0 & 0 & 1 & 0 \end{pmatrix}$$

Next we obtain the matrix $D = A_2 = U_2 C V_2$

$$D = \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & -1 & 0 & -1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 & 2 & -2 & -1 \\ 1 & 1 & -3 & 1 \\ 0 & -1 & 0 & -1 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} 1 & 0 & 0 & 0 \\ 0 & -1 & 0 & -1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} 0 & -2 & -2 & -3 \\ -1 & 1 & 2 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}.$$

Finally the Frobenius form $F[A] = A_1 = U_1 D V_1$,

$$F[A] = \begin{pmatrix} -1 & 1 & 2 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} 0 & -2 & -2 & -3 \\ -1 & 1 & 2 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix} \begin{pmatrix} -1 & 1 & 2 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{pmatrix} = \begin{pmatrix} 1 & 4 & 2 & 3 \\ 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{pmatrix}.$$

Thus the Characteristic polynomial of A is :

$$K_A(\lambda) = x^4 - x^3 - 4x^2 - 2x - 3$$

 $\begin{array}{l} A = input('Enter \ the \ square \ matrix \ A \ : \ '); \\ m = size(A); \ N = m(1); \ b = [1]; \ B = zeros(N); \ i = 1; \\ while \ i < N, \\ J = eye(N); h = A(N - i + 1, N - i) \\ while \ h == 0; \\ c = A(N - i + 1, 1 : N - i); \ z = norm(c, inf); \\ if \ z = 0; \\ k = 1; \ r = 0; \\ while \ r == 0 \ \& \ k < N - i; \\ r = r + c(N - i - k); \ k = k + 1; \\ J(N - i, N - i) = 0; \ J(N - i, N - i - k + 1) = 1; \\ J(N - i - k + 1, N - i - k + 1) = 0; \ J(N - i - k + 1, N - i) = 1, \end{array}$

$$\begin{array}{l} A = J * A * J; \ k = k + 1; \\ end \\ else \\ b = conv(b, [1 - A(N - i + 1, N - i + 1 : N)]); \\ B = A(1 : N - i, 1 : N - i); A = B, N = N - i; \\ end \\ h = A(N - i + 1, N - i); \\ end \\ U = eye(N); \ V = eye(N); \\ U(N - i, :) = A(N - i + 1, :); \\ V(N - i, :) = -A(N - i + 1, :)/A(N - i + 1, N - i); \ V(N - i, N - i) = 1/A(N - i + 1, N - i); \\ A = U * A * V; \\ i = i + 1; \\ end; \\ b = conv(b, \ [1 - A(N - i + 1, N - i + 1 : N)]); \ disp(' \ '), \\ disp('The \ Characteristic \ polynomial \ looks \ like \ : \ '), \ disp(' \ '), \\ disp(['K_A(x) = x \wedge n + c(1)x \wedge (n - 1), + ... + c(n - 1)x + c(n)']), \ disp(' \ '), \\ disp(b), \ disp(' \ ') \end{array}$$

\frac{1}{2} The Method of Krylov. Let *A* be an $n \times n$ matrix. For any *n*-dimensional nonzero column vector *v* we associate its successive transforms

$$v_k = A^k v$$
 $(k = 0, 1, 2, ...),$

this sequence of vectors is called the Krylov sequence associated to the matrix A and the vector v.

At most *n* vectors of the sequence v_0, v_1, v_2, \ldots will be linearly independent. Suppose for some $r = r(v) \leq n$, the vectors $v_0, v_1, v_2, \ldots, v_r$ are linearly independent and the vector v_{r+1} is a linear combination of the preceding ones. Hence there exists a monic polynomial

$$\phi(\lambda) = c_0 + c_1 \lambda + c_2 \lambda^2 + \dots + c_{r-1} \lambda^{r-1} + \lambda^r$$

such that

$$\phi(A)v = (c_0I_n + c_1A + \dots + c_{r-1}A^{r-1} + A^r)v = c_0v_0 + c_1v_1 + \dots + c_{r-1}v_r + c_rv_{r+1} = \theta.$$

The polynomial $\phi(\lambda)$ is said to annihilate v and to be minimal for v. If $\omega(\lambda)$ is another monic polynomial which annihilates v,

 $\omega(A)v = 0\,,$

then $\phi(\lambda)$ divides $\omega(\lambda)$. To show that; suppose

$$\omega(\lambda) = \gamma(\lambda)\phi(\lambda) + \rho(\lambda),$$

where $\rho(\lambda)$ is the remainder after dividing ω by ϕ , hence of degree strictly less than r, it follows that

$$\rho(A)v = 0.$$

But $\phi(\lambda)$ is minimal for v, hence $\rho(\lambda) = 0$.

Now of all vectors v there is at least one vector for which the degree v is maximal, since for any vector $v, r(v) \leq n$. We call such vector a maximal vector.

A monic polynomial $\mu_A(\lambda)$ is said to be the minimal polynomial for A, if $\mu_A(\lambda)$ is monic and of minimum degree satisfying

$$\phi(A) = Z_n.$$

Theorem 1. Let A be an $n \times n$ matrix and let $\phi(\lambda)$ be a minimal polynomial for a maximal vector v. Then $\phi(\lambda)$ is the minimal polynomial for A.

Proof. Consider any vector u such that u and v are linearly independent. Let $\psi(\lambda)$ be its minimal polynomial. If ω is the lowest common multiple of ϕ and ψ , then ω annihilates every vector in the plane of u and v, since

$$\omega(A)(\alpha u + \beta v) = \alpha \omega(A)u + \beta \omega(A)v = \theta.$$

Hence ω contains as a divisor the minimal polynomial of every vector in the plane. But ω is of degree 2n at most, hence has only finitely many divisors. Since there are infinitely many pairs of linearly independent vectors in the plane and finitely many divisors of ω , there is a pair of linearly independent vectors x and y in this plane with the same minimal polynomial. This polynomial also annihilates v since v is on this plane. Therefore ϕ is minimal for every vectors in the plane of u and v, and since u was any vector whatever, other than v, ϕ annihilates every n-dimensional vector.

Since ϕ annihilates every vector, it annihilates in particular every vector e_i , hence

$$\phi(A)I = \phi(A) = Z_n.$$

Thus $\phi(\lambda) = \mu_A(\lambda)$ is the minimal polynomial for A.

If the minimal polynomial and the characteristic polynomial of a matrix are equal, then they may be found by the use of Krylov's sequence. To produce the characteristic polynomial of A by Krylov method, first choose an arbitrary *n*-dimensional nonzero column vector v such as e_1 , then use the Krylov sequence to define the matrix

$$V = [v, Av, A^2v, \dots, An - 2v, A^{n-1}v] = [v_0, v_1, v - 2, \dots, v_{n-2}, v_{n-1}].$$

If the matrix V has rank n, then the system $Vc = -v_n$ has a unique solution

$$c^{t} = (c_0, c_1, c_2, \cdots, c_{n-1}).$$

The monic polynomial

$$\phi(\lambda) = c_0 + c_1 \lambda + c_2 \lambda^2 + \dots + c_{n-1} \lambda^{n-1} + \lambda^n$$

which annihilates v is the characteristic polynomial of A. If the system $Vc = -v_n$ does not have a unique solution, then change the initial vector and try for example with e_2 .

Examples. Compute the characteristic polynomials of the following matrices:

$$A = \begin{pmatrix} 1 & 2 & 1 & -1 \\ 1 & 0 & 2 & 1 \\ 2 & 1 & -1 & 3 \\ 4 & -5 & 0 & 4 \end{pmatrix} \quad and \quad B = \begin{pmatrix} 1 & 2 & -3 & 1 \\ 1 & 0 & -2 & 1 \\ 1 & -3 & -1 & 3 \\ 1 & 0 & 1 & -2 \end{pmatrix}.$$

Choosing the initial vector $v = \begin{pmatrix} 1 \\ 0 \\ 0 \\ 0 \end{pmatrix}$ for both matrices, we obtain

$$V_A = [v, Av, A^2v, A^3v] = \begin{pmatrix} 1 & 1 & 1 & 17\\ 0 & 1 & 9 & 42\\ 0 & 2 & 13 & 43\\ 0 & 4 & 15 & 19 \end{pmatrix} \quad \text{and} \quad V_B = [v, Bv, B^2v, B^3v] = \begin{pmatrix} 1 & 1 & 1 & 1\\ 0 & 1 & 0 & 1\\ 0 & 1 & 0 & 1\\ 0 & 1 & 0 & 1 \end{pmatrix}.$$

The Method of Krylov

The matrix V_A is nonsingular, hence $c_A = -V_A^{-1}A^4v = \begin{pmatrix} -87\\ 28\\ 2\\ -4 \end{pmatrix}$. From c_A we obtain the characteristic polynomial of A which is

$$K_A(\lambda) = -87 + 28\lambda + 2\lambda^2 - 4\lambda^3 + \lambda^4.$$

The matrix V_B is singular, so we need another initial vector such as $v = \begin{pmatrix} 0 \\ 1 \\ 0 \\ 0 \end{pmatrix}$. The new

matrix
$$V_B = \begin{pmatrix} 0 & 2 & 11 & 11 \\ 1 & 0 & 8 & 0 \\ 0 & -3 & 5 & -21 \\ 0 & 0 & -1 & 18 \end{pmatrix}$$
 is invertible, so $c_B = -V_B^{-1}A^4v = \begin{pmatrix} 9 \\ -2 \\ -10 \\ 2 \end{pmatrix}$. From the

solution c_B we obtain the characteristic polynomial of B which is

$$K_B(\lambda) = 9 - 2\lambda - 10\lambda^2 + 2\lambda^3 + \lambda^4.$$

Remark. The minimal polynomial and the characteristic polynomial of the matrix

$$A = \begin{pmatrix} 1 & 2 & 3 & 4 \\ 1 & 2 & 3 & 4 \\ 1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix}$$

are

$$m_A(\lambda) = \lambda^3 - 3\lambda^2 - 7\lambda$$
 and $K_A(\lambda) = \lambda^4 - 3\lambda^3 - 7\lambda^2$,

respectively. Therefore by choosing any initial vector v, the matrix $V_A = [v, Av, A^2v, A^3v]$ will always be singular. This means that the Krylov sequence will never produce the characteristic polynomial $K_A(\lambda)$.

Matlab Program

 $A = input('Enter \ a \ square \ matrix \ A \ : \ ');$ m = size(A); n = m(1); V = zeros(n, n);DL1 = ['Enter an initial ', int2str(n) , '-dimensional row vector v0 = '];v0 = input(DL1);z = 0; k = 1;while z == 0 & k < 5w = v0; V(:, 1) = w;for i = 2: n, w = A * w; V(:, i) = w; end, *if* $det(V) \sim = 0$; k = 8; c = -inv(V) * A * w; elsewhile k < 5v0 = input('The matrix V is singular, please enter another initial row vector <math>v0 : ');k = k + 1;end;end;z = det(V);end: *if* k == 5;disp('Sorry, the Krylov method is not suited for this matrix.'), disp(''), else; disp('The Characteristic polynomial looks like : '), disp(' '), $disp(['K_A(x) = c(0) + C(1)x + c(2)x \land 2 + \dots + c(n-1)x \land (n-1) + x \land n']), disp(''),$ $disp('The \ coefficients \ list \ c(k) \ is \ : \ '), disp(' \ '),$ disp([c',1])end;

California State University, East Bay

Page 14