

Math 642:550 — Summer 2003
MTTh 6:15–8:45 PM Hill 525
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Supplement 4: Finding eigenvectors

1. Introduction

Important **theoretical** results are that: (1) eigenvalues are characterized as the roots of the **characteristic polynomial**; and (2) the characteristic polynomial may be expressed as a determinant. If you have an eigenvalue λ , then the eigenvectors of a matrix M with eigenvalue λ are the nonzero vectors in the nullspace of $M - \lambda I$. If you are unable to find such vectors, then **you have made a mistake somewhere**. Mistakes in this work are common, so you should organize your work to include checks that allow you to discover your mistakes before showing them to anyone else.

This is not the only way to find eigenvalues or eigenvectors. There are many examples where some eigenvalues can be found **without** finding the characteristic polynomials. There are even examples where eigenvalues are found by **first** finding the eigenvector v and then noting the scale factor relating v and Mv . It should also be noted that the failure of the attempt to find such a scale factor is a **proof** that v is not an eigenvector of M .

2. Triangular matrices

Since the determinant of a triangular matrix is the product of the diagonal entries, the characteristic polynomial of

$$\begin{bmatrix} 1 & -1 & 3 \\ 0 & 2 & 5 \\ 0 & 0 & -4 \end{bmatrix}$$

is $(1 - \lambda)(2 - \lambda)(-4 - \lambda)$. There is no reason to expand this product; the roots of the characteristic polynomial are more valuable than the coefficients. The eigenvalues are 1, 2 and -4 . We now turn our attention to finding eigenvectors.

The eigenvectors for $\lambda = 1$ lie in the nullspace of

$$M_1 = \begin{bmatrix} 0 & -1 & 3 \\ 0 & 1 & 5 \\ 0 & 0 & -5 \end{bmatrix}.$$

This matrix is already in echelon form, so we read the rows from the bottom to find properties of v with $M_1 v = 0$. Since -5 times the third entry of v is zero, the third entry of v is zero. The second row now tells us that the second entry of v is zero. Now, the first row tells us only that $0 = 0$. **There is no restriction on the first entry**. The nullspace consists of all multiples of $(1, 0, 0)$. We may take any nonzero multiple of this as an eigenvector. It is usually best to take $(1, 0, 0)$ itself. Although this is the easiest eigenvector to find, it is often overlooked because few matrices with a zero first column are met in a first course on Linear Algebra.

The eigenvectors for $\lambda = 2$ lie in the nullspace of

$$\begin{bmatrix} -1 & -1 & 3 \\ 0 & 0 & 5 \\ 0 & 0 & -6 \end{bmatrix}.$$

As before, the third row says that the third entry of an eigenvector is zero. This time, the second row says nothing new. Then, the first row says that the first entry of the eigenvector is the negative of the second entry. Any nonzero vector with this property may be used. To keep the expression simple, we take $(1, -1, 0)$.

The eigenvectors for $\lambda = -4$ lie in the nullspace of

$$\begin{bmatrix} 5 & -1 & 3 \\ 0 & 6 & 5 \\ 0 & 0 & 0 \end{bmatrix}.$$

Equations giving ratios of entries in the eigenvector are easily found. If the third entry is taken to be -24 , the other entries will be integers. Indeed, the eigenvector is $(23, 20, -24)$ — or any nonzero multiple. Since the scaling of an eigenvector is arbitrary, a rational vector is usually scaled to have integer entries.

3. Projections

Example 2 in Section 5.1 uses the geometric description of projections to identify the nullspaces of P and of $P - I$ and to show that their sum is the whole space. An approach that applies more generally is to use the geometry to show that a projection matrix P satisfies $P^2 = P$. That is, any vector Px in the range of the projection must be projected into itself, so that $P^2x = Px$ for all x . If the matrix $P^2 - P$ takes each vector to zero, applying it to the standard basis shows that each column is the zero vector, so every entry is zero,

If v is an eigenvector with eigenvalue λ , then $Pv = \lambda v$ and $P^2v = P(\lambda v) = \lambda(Pv) = \lambda(\lambda v) = \lambda^2 v$. Thus, $\lambda^2 v = \lambda v$ or $(\lambda^2 - \lambda)v = 0$. Since v is a nonzero vector, $\lambda^2 - \lambda = 0$. The only solutions of this are $\lambda = 0$ and $\lambda = 1$.

Since $P(I - P)x = 0$ for all vectors x , if $y = (I - P)x$, then $P y = P(I - P)x = 0$, so y is either the zero vector or an eigenvector with eigenvalue 0. Similarly, each Px is either the zero vector or an eigenvector with eigenvalue 1. However x is the sum of these two vectors. Thus the sum of the two eigenspaces is the whole space, and there is a basis of eigenvectors.

If $f(M) = 0$ for some polynomial f , the above argument generalizes to show that $f(\lambda) = 0$ for any eigenvalue. If f has only simple roots then, for any factorization of f into two factors, the Euclidean Algorithm for polynomials produces multiples of the factors whose sum is 1. When evaluated at P , these multiples give **projections**. Induction on this construction shows again that the whole space is a sum of eigenspaces.

A related result, equally easily proved, is that

$$Mv = \lambda v \text{ implies } f(M)v = f(\lambda)v$$

for all polynomials f . An important special case notes that if you add c to the diagonal of M , you add c to all eigenvalues **without changing the eigenvectors**. This is explored in exercises 5.1.3 and 5.1.7. In particular, this shows that **there is nothing special about zero as an eigenvalue**, since there are closely related matrices having the same eigenvectors where one has zero as an eigenvalue and the other does not.

4. Markov matrices

A **Markov matrix** M is an n by n matrix (all matrices in this part of the course are square matrices) with all entries nonnegative and the sum of the entries in each **column** equal to 1. The transpose of a Markov matrix M^T has the sum of each **row** equal to 1. If $v = (1, 1, \dots, 1)$, this gives $M^T v = v$. Thus, v is an eigenvector of M^T with eigenvalue 1. Since we have the eigenvector, we know that 1 is an eigenvalue of M^T .

It is always true that M and M^T have the same eigenvalues, so 1 is an eigenvalue of M . However, this time we don't know the eigenvector. However, **we are sure** that $M - I$ has a nontrivial nullspace, so we proceed to compute the nullspace. It can be shown that the eigenvector found in this way will have **all entries nonnegative**. If normalized so that the **sum of the entries** is 1, it is called the **limiting distribution** of the process represented by M . We make no attempt to find the other eigenvalues or eigenvectors. Statement **5I** of the textbook asserts that no eigenvalue exceeds 1 in absolute value (although some may be complex numbers).

Taking each entry of a 3 by 3 matrix to be a fraction with denominator 10 allows $220^3 = 10648000$ — more than ten million — examples for which the computation will be manageable.

4.1 Example

Let

$$M = \begin{bmatrix} 0.2 & 0.4 & 0.6 \\ 0.5 & 0.3 & 0.1 \\ 0.3 & 0.3 & 0.3 \end{bmatrix}.$$

Then

$$M - I = \begin{bmatrix} -0.8 & 0.4 & 0.6 \\ 0.5 & -0.7 & 0.1 \\ 0.3 & 0.3 & -0.7 \end{bmatrix}.$$

To solve $(M - I)v = 0$, we first scale all rows by multiplying by 10 to get integer entries. Then, the second and third rows are multiplied by 8 to make their leading entries divisible by the pivot. This gives the array

$$\begin{bmatrix} -8 & 4 & 6 \\ 40 & -56 & 8 \\ 24 & 24 & -56 \end{bmatrix}$$

Pivoting:

$$\begin{bmatrix} -8 & 4 & 6 \\ 0 & -36 & 48 \\ 0 & 36 & -48 \end{bmatrix}$$

The second and third rows are now negatives of one another. Each gives the ratio of x_2 to x_3 and then the first row gives x_1 . In this case, we get $(x_1, x_2, x_3) = (23, 19, 18)$.

Note that only the matrix of coefficients of the left side of the equation is written when we use Gaussian elimination to solve the equations to find the eigenvector. This is because we know that the right side will **always be zero**, no matter what row operations we perform. (On the other hand, I have seen students insist on writing a right side and accidentally introduce a nonzero quantity in one of the steps.)

5. Exercise 1

Find the limiting distribution of the Markov matrix

$$\begin{bmatrix} 0.1 & 0.5 & 0.2 \\ 0.4 & 0.2 & 0.7 \\ 0.5 & 0.3 & 0.1 \end{bmatrix}.$$

6. Companion matrices

Suppose that a matrix has the form

$$\begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ c & b & a \end{bmatrix}.$$

Such a matrix has an eigenvector of the form $(1, x, x^2)$ since

$$\begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ c & b & a \end{bmatrix} \begin{bmatrix} 1 \\ x \\ x^2 \end{bmatrix} = \begin{bmatrix} x \\ x^2 \\ c + bx + ax^2 \end{bmatrix} = \begin{bmatrix} x \\ x^2 \\ x^3 \end{bmatrix} = \begin{bmatrix} 1 \\ x \\ x^2 \end{bmatrix} x$$

if $x^3 = ax^2 + bx + c$. If this polynomial has distinct roots, then we have found a basis of eigenvectors, so the matrix can be diagonalized (as discussed in Section 5.2 of the textbook). All three roots of the polynomial are eigenvalues, so this polynomial divides the characteristic polynomial. Since the polynomials have the same degree, the quotient is a constant, and consideration of the coefficient of x^3 shows that the characteristic polynomial is $-x^3 + ax^2 + bx + c$.

This matrix is called the **companion matrix** of the polynomial $x^3 - ax^2 - bx - c$. There is an obvious generalization giving an n by n companion matrix of a polynomial of degree n .

Remark. It is also true the characteristic polynomial of the companion matrix of a monic polynomial $P(x)$ of degree n is **always** $(-1)^n P(x)$ and that the eigenvectors **always** have the form $(1, x, \dots, x^{n-1})$. We will not prove this here, but some clues will be given in Exercise 2.

A related matrix is the **Leslie matrix** arising in models of population growth. (A special case makes an appearance in Exercise 5.3.4 of the textbook.) The basic idea is to consider a vector v whose i^{th} entry is the count of individuals in the i^{th} year of life at a particular time and to form a matrix M such that Mv describes a similar vector one year later. The next year's count consists of **survivors** who are one year older and **newborn** individuals in their first year of life. The survivors contribute entries between 0 and 1 to the sub-diagonal of M , and the newborns give nonnegative entries in the first row in a column indicating the age of the parent.

7. Exercise 2

By direct expansion of $\det(M - \lambda I)$, find the characteristic polynomial of

$$M = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & -2 \end{bmatrix}.$$

For each eigenvalue of M , find all eigenvectors. Then, form M^2 and find its eigenvalues and eigenvectors. Every eigenvector of M will be seen to be an eigenvector of M^2 , but you should find eigenvectors of M^2 that are not eigenvectors of M . You can now diagonalize M^2 although M cannot be diagonalized.

8. The Power Method

The basic computational method for finding eigenvalues and eigenvectors is the **power method**. Section 7.3 is devoted to this method and several of its refinements, and we will return to it later in the course. For now, it will suffice to illustrate the method. As an example, consider

$$M = \begin{bmatrix} 0.4 & 0.2 & 0.7 \\ 0.5 & 0.3 & 0.1 \\ 0.1 & 0.5 & 0.2 \end{bmatrix}.$$

This has the same rows as the matrix appearing in the Markov matrix exercise, in a different order, but you will find that the limiting distribution is quite different. Iteration of $v_{n+1} = Mv_n$ for various choices of v_0 will be illustrated in lecture. Since this is a Markov matrix, the sum of the entries in v_n is constant. We can check the result of the power method for this example because we are able to find an exact solution that is rational. If we multiply by the denominator (124 in this case), our computed values should be very close to the integer numerators.

With other matrices, it would be necessary to rescale each v_n . The scale factors will converge to the dominant eigenvalue if there is one. A simple scaling is to make the first entry of the vector equal to 1. This is adequate for interactive use on a calculator, since it will be easy to detect if it is inappropriate (for example, if that entry of the eigenvalue is much smaller than the other entries). If all entries of the matrix are positive, the iteration converges reliably to a positive eigenvector. For other matrices, the eigenvalues of largest absolute value may be complex. In this case, the iteration will not converge, although in some cases it will appear to cycle. Some examples are

$$\begin{bmatrix} 5 & -2 & 1 \\ 3 & 2 & -1 \\ -2 & 3 & 4 \end{bmatrix} \quad \text{and} \quad \begin{bmatrix} 5 & 2 & 1 \\ 3 & 2 & 1 \\ 2 & 3 & 4 \end{bmatrix}.$$

The first of these has eigenvalues approximately $3.3 + 3.0i$, of absolute value 4.46 that slightly dominate the real eigenvalue of 4.42. The second matrix has three real eigenvalues (approximately 7.64, 2.92, and 0.45). The second iteration clearly converges, with the analysis of the method indicating that there will be an additional two places of accuracy every five iterations. For the first matrix, the lack of convergence will be clear rather quickly, but the power method calculation suggests no remedy. when we return to the topic in Chapter 7, better methods for dealing with this matrix will be met.

End of Supplement