

ES111 Mathematical Methods in the Earth Sciences  
Lecture Outlines #14  
Eigenvectors and Eigenvalues

Eigenanalysis characterizes the spatial geometry of square matrices, affording insight into their effect as transforms, inverses, etc. There is a massive literature built up around this topic; our discussion will be brief and focused on eigenanalysis in strain theory.

Eigenanalysis involves two things: eigenvectors and eigenvalues. What are they? Well, both are defined by a single vector equation:

$$\mathbf{Ax} = \lambda \mathbf{x}$$

where  $\mathbf{A}$  is a square matrix,  $\mathbf{x}$  is an *eigenvector* of  $\mathbf{A}$  and  $\lambda$  is the associated *eigenvalue* (there may be more than one eigenvector per eigenvalue).  $\lambda$  is a scalar, thus this equation tells us that  $\mathbf{A}$  does not alter the direction of its eigenvectors, it only scales their length. Thus the eigenvectors of  $\mathbf{A}$  define its *characteristic directions*.

How do we obtain the eigenvectors and eigenvalues of a matrix? The answer is pretty simple. First we rewrite the above equation as:

$$\mathbf{Ax} - \lambda \mathbf{x} = \mathbf{0}$$

or

$$(\mathbf{A} - \lambda \mathbf{I})\mathbf{x} = \mathbf{0}$$

Aha! For there to be a solution of this equation, the matrix in parenthesis must have a null space. If it has a null space, it can't be full rank and its determinant must be zero! Thus

$$\det(\mathbf{A} - \lambda \mathbf{I}) = 0$$

provides us with a polynomial in terms of  $\lambda$  that can be solved for the eigenvalues of  $\mathbf{A}$ . If  $\mathbf{A}$  is  $n$  by  $n$ , the polynomial has terms up to  $\lambda^n$  and will have from 1 to  $n$  distinct roots, corresponding to the eigenvalues of  $\mathbf{A}$ .

The eigenvalues of  $\mathbf{A}$  have several unique properties:

1. The sum of elements along the main diagonal of  $\mathbf{A}$  (a quantity known as the trace of  $\mathbf{A}$ ) equals the sum of eigenvalues (repeating repeated roots).

$$\text{Trace } \mathbf{A} = \sum_{i=1}^n a_{ii} = \sum_{i=1}^n \lambda_i$$

2. The determinant of  $\mathbf{A}$  is equal to the serial product of eigenvalues.

$$\det \mathbf{A} = \prod_{i=1}^n \lambda_i$$

This has an important corollary. If  $\mathbf{A}$  is singular (not full rank), then it has a zero determinant and must have one or more zero eigenvalues. This means it has a null space since a zero eigenvalue implies

$$\mathbf{Ax} = \mathbf{0}$$

The next question is, of course, how do we obtain eigenvectors? The answer is simple. We plug an eigenvalue into the equation

$$(\mathbf{A} - \lambda \mathbf{I})\mathbf{x} = \mathbf{0}$$

and solve it for the elements of  $\mathbf{x}$ . The length of the vector is not determined by the above equation since only  $n - 1$  of the  $n$  elements of  $\mathbf{x}$  are determined. As a result, it is typical to normalized  $\mathbf{x}$  to unit length.

If  $\mathbf{A}$  is full rank, then the  $n$  eigenvectors of  $\mathbf{A}$  form a *basis* for  $n$ -dimensional space. If  $\mathbf{A}$  is not full rank, there are one or more zero eigenvalues and the eigenvectors do not fully span  $n$ -dimensional space.

If  $\mathbf{A}$  is symmetric and full rank, the eigenvectors of  $\mathbf{A}$  form an *orthonormal basis* for  $n$ -dimensional space, meaning they span the space and obey

$$\mathbf{x}_i^T \mathbf{x}_j = \delta_{ij}$$

implying that the eigenvectors are orthogonal to one another (note that the eigenvectors are scaled such that they all have unit length).

*Matrix Diagonalization:*

An  $n$  by  $n$  full rank matrix  $\mathbf{A}$  can be made diagonal via:

$$\mathbf{D} = \mathbf{X}^{-1} \mathbf{A} \mathbf{X}$$

where  $\mathbf{X}$  is composed of the eigenvectors of  $\mathbf{A}$ , *i.e.*,

$$\mathbf{X} = (\mathbf{x}_1 \quad \mathbf{x}_2 \quad \dots \quad \mathbf{x}_n)$$

If  $\mathbf{A}$  is symmetric, then  $\mathbf{X}$  is a unitary or orthogonal matrix such that

$$\mathbf{X}^{-1} = \mathbf{X}^T$$

hence,

$$\mathbf{D} = \mathbf{X}^T \mathbf{A} \mathbf{X}$$

This last result has an important role to play in strain analysis.

*2D Strain:*

Assume that the initial position of a point in an undeformed medium is  $(x,y)$  and its position after strain has occurred is  $(x',y')$ . For small strains,  $(x',y')$  can be related to  $(x,y)$  by an *Affine Transformation*:

$$ax + by = x'$$

$$cx + dy = y'$$

or  $\mathbf{A} \mathbf{x} = \mathbf{x}'$  where

$$\mathbf{A} = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \quad \mathbf{x} = \begin{pmatrix} x \\ y \end{pmatrix} \quad \text{and} \quad \mathbf{x}' = \begin{pmatrix} x' \\ y' \end{pmatrix}$$

This is an example of a linear transformation as discussed in Chapter 7.15 of K. As written,  $\mathbf{A}$  is perfectly general. Three canonical forms of the strain matrix  $\mathbf{A}$  are:

1. Rigid Rotation

$$\mathbf{A} = \begin{pmatrix} \cos & \sin \\ -\sin & \cos \end{pmatrix}$$

2. Simple Shear

$$\mathbf{A} = \begin{pmatrix} 1 & \\ 0 & 1 \end{pmatrix}$$

Here the shear is parallel to the  $x$  axis.  $\gamma$  is referred to as the *shearstrain* and  $\gamma = \tan \theta$  defines  $\theta$  which is called the *angular shear strain*.

### 3. Pure Shear

$$\mathbf{A} = \begin{pmatrix} a & 0 \\ 0 & d \end{pmatrix}$$

$a$  or  $d > 1$  implies dilatation (expansion),  $< 1$  implies compression.

The serial product of these three transformations can produce any linear transformation, *i.e.*, any infinitesimal strain field.

#### *Strain Ellipses:*

Imagine of a locus of points defining a circle which undergoes some strain,

$e_1$  and  $e_2$  are the *principlestrains* or *principal extensions*. Given the strain matrix  $\mathbf{A}$ , we can use matrix diagonalization to obtain the principal strains and the principal *strain axes* PROVIDED there is no simple shear involved. Simple shear does not have a full eigenvector basis. Since pure shear is characterized by a symmetric strain matrix, diagonalizing it is fairly simple. In 2D:

$$\mathbf{A} = \mathbf{S}^T \mathbf{\Lambda} \mathbf{S}$$

Here  $\mathbf{S}$  contains the eigenvectors of  $\mathbf{A}$  normalized to unit length.  $\mathbf{\Lambda}$  is a diagonal matrix that has the associated eigenvalues of  $\mathbf{A}$  along the diagonal,

$$\mathbf{\Lambda} = \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix}$$

where we have chosen to number the eigenvalues and vectors such that  $\lambda_1 \geq \lambda_2$ . We can rearrange the above equation, finding

$$\mathbf{A} = \mathbf{S} \mathbf{\Lambda} \mathbf{S}^T$$

Written this way, the eigenvalues and vectors of  $\mathbf{A}$  have simple interpretations in terms of strain. Since  $\lambda_1 \geq \lambda_2$ ,

$$\lambda_1 = 1 + e_1$$

or

$$e_1 = \lambda_1 - 1$$

is the major axis extension and  $\mathbf{x}_1$  is the major axis orientation. Likewise

$$\lambda_2 = 1 + e_2$$

or

$$e_2 = \lambda_2 - 1$$

is the minor axis extension and  $\mathbf{x}_2$  is the minor axis orientation. Why? Think of strain as evolving by small steps of growth and/or contraction along the major and minor axes. Since these axes are not rotated by  $\mathbf{A}$ , a circle evolves to an ellipse. In other words,

repeatedly applying  $\mathbf{A}$  to a position vector parallel to an eigenvector will not change the direction of the vector, only its length. It will slowly grow or contract depending on the strain matrix.

Note that a general square matrix  $\mathbf{A}$  can be factored into a sum of two matrices, one symmetric, the other skew-symmetric:

$$\mathbf{A} = \mathbf{S} + \mathbf{R}$$

where  $\mathbf{S}$  is symmetric

$$\mathbf{S} = \frac{1}{2}(\mathbf{A} + \mathbf{A}^T)$$

and  $\mathbf{R}$  is skew symmetric

$$\mathbf{R} = \frac{1}{2}(\mathbf{A} - \mathbf{A}^T)$$

In strain analysis, we typically deal with  $\mathbf{S}$ , rather than  $\mathbf{A}$ , since it has no rigid rotation in it.