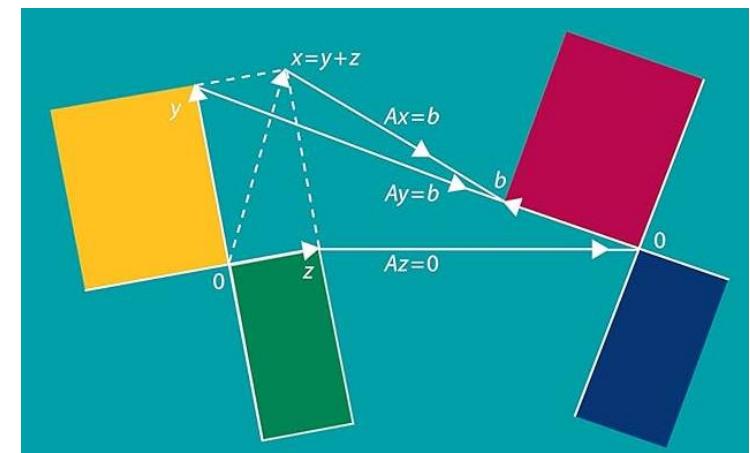


# Eigenvalues and Eigenvectors

## (Linear Algebra)

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When a square matrix  $A$  acts upon a vector  $x$ , it generally outputs a new vector  $Ax$ . Usually this new vector will be stretched and rotated. For example, if we take the matrix

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

and apply it to the vector  $\begin{pmatrix} 0 \\ 1 \end{pmatrix}$  we get:

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

If we apply  $A$  to the vector  $\begin{pmatrix} 1 \\ 1 \end{pmatrix}$  we get:

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

if we apply  $A$  to the vector  $\begin{pmatrix} 1 \\ 0 \end{pmatrix}$  we get:

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

The matrix  $A$  leaves the vector  $\begin{pmatrix} 1 \\ 0 \end{pmatrix}$  unchanged! In particular, it does not rotate the vector. When a matrix  $A$  acts upon a vector and does not rotate it, we have  $A\mathbf{x} = \lambda\mathbf{x}$ , where  $\lambda$  is a scaling factor. In our example  $\lambda = 1$ . We call such a vector an *eigenvector* for the matrix  $A$ , and the associated scaling factor  $\lambda$  an *eigenvalue*.

# Definition

Let  $A$  be an  $n \times n$  matrix. If there exist a real value  $\lambda$  and a non-zero  $n \times 1$  vector  $x$  satisfying,

$$Ax = \lambda x$$

then

we refer to  $\lambda$  as an eigenvalue of  $A$ , and  $x$  as an eigenvector of  $A$  corresponding to  $\lambda$ .

The basic equation for eigenvectors and eigenvalues is

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

where  $A$  is a matrix and  $\lambda$  is a number. One property we see right away is

$$A^2\mathbf{x} = \lambda A\mathbf{x} = \lambda^2\mathbf{x}$$

and in general

$$A^n\mathbf{x} = \lambda^n\mathbf{x}.$$

So, the eigenvectors of  $A^n$  are the same as the eigenvectors of  $A$ , while the eigenvalues for  $A^n$  are the eigenvalues for  $A$  raised to the  $n$ th power.

# Purpose of Learning in Computer Science

- Data Compression and Dimensionality Reduction:
  - reduce the dimensionality of large datasets, increasing interpretability while minimizing information loss.
- Machine Learning:
  - Feature Extraction and Selection
- Computer Vision and Image Processing:
  - Image Compression and Face Recognition
- Natural Language Processing (NLP):
  - Word Embedding

# How to calculate?

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

then

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

So, the matrix  $(A - \lambda I)$  has a nontrivial nullspace, and therefore must be singular. So,

$$\det(A - \lambda I) = 0.$$

So, if  $\lambda$  is an eigenvalue of  $A$  then  $\det(A - \lambda I) = 0$ . It turns out that this equation can be used to calculate *every* eigenvalue. The equation  $\det(A - \lambda I) = 0$  will be a polynomial equation in  $\lambda$ , and its roots will give us all the eigenvalues. We call this polynomial equation the *characteristic equation* of  $A$ .

Eigenvalues first. If  $(A - \lambda I)\mathbf{x} = \mathbf{0}$  has a nonzero solution,  $A - \lambda I$  is not invertible. **The determinant of  $A - \lambda I$  must be zero.** This is how to recognize an eigenvalue  $\lambda$ :

**Eigenvalues** The number  $\lambda$  is an eigenvalue of  $A$  if and only if  $A - \lambda I$  is singular.

**Equation for the  $n$  eigenvalues of  $A$**

$$\det(A - \lambda I) = 0. \quad (5)$$

This “*characteristic polynomial*”  $\det(A - \lambda I)$  involves only  $\lambda$ , not  $\mathbf{x}$ . Since  $\lambda$  appears all along the main diagonal of  $A - \lambda I$ , the determinant in (5) includes  $(-\lambda)^n$ . Then equation (5) has  $n$  solutions  $\lambda_1$  to  $\lambda_n$  and  $A$  has  $n$  eigenvalues.

**An  $n$  by  $n$  matrix has  $n$  eigenvalues (repeated  $\lambda$ 's are possible !)** Each  $\lambda$  leads to  $\mathbf{x}$ :

**For each eigenvalue  $\lambda$  solve  $(A - \lambda I)\mathbf{x} = \mathbf{0}$  or  $A\mathbf{x} = \lambda\mathbf{x}$  to find an eigenvector  $\mathbf{x}$ .**

**Example 4**  $A = \begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix}$  is already singular (zero determinant). Find its  $\lambda$ 's and  $\mathbf{x}$ 's.

When  $A$  is singular,  $\lambda = 0$  is one of the eigenvalues. The equation  $A\mathbf{x} = 0\mathbf{x}$  has solutions. They are the eigenvectors for  $\lambda = 0$ . But  $\det(A - \lambda I) = 0$  is the way to find *all*  $\lambda$ 's and  $\mathbf{x}$ 's. Always subtract  $\lambda I$  from  $A$ :

*Subtract  $\lambda$  along the diagonal to find*  $A - \lambda I = \begin{bmatrix} 1 - \lambda & 2 \\ 2 & 4 - \lambda \end{bmatrix}$ . (6)

*Take the determinant “ $ad - bc$ ” of this 2 by 2 matrix.* From  $1 - \lambda$  times  $4 - \lambda$ , the “ $ad$ ” part is  $\lambda^2 - 5\lambda + 4$ . The “ $bc$ ” part, not containing  $\lambda$ , is 2 times 2.

$$\det \begin{bmatrix} 1 - \lambda & 2 \\ 2 & 4 - \lambda \end{bmatrix} = (1 - \lambda)(4 - \lambda) - (2)(2) = \lambda^2 - 5\lambda. \quad (7)$$

**Set this determinant  $\lambda^2 - 5\lambda$  to zero.** One solution is  $\lambda = 0$  (as expected, since  $A$  is singular). Factoring into  $\lambda$  times  $\lambda - 5$ , the other root is  $\lambda = 5$ :

$$\det(A - \lambda I) = \lambda^2 - 5\lambda = 0 \quad \text{yields the eigenvalues } \lambda_1 = 0 \quad \text{and} \quad \lambda_2 = 5.$$

Now find the eigenvectors. Solve  $(A - \lambda I)\mathbf{x} = \mathbf{0}$  separately for  $\lambda_1 = 0$  and  $\lambda_2 = 5$ :

$$(A - 0I)\mathbf{x} = \begin{bmatrix} 1 & 2 \\ 2 & 4 \end{bmatrix} \begin{bmatrix} y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad \text{yields an eigenvector} \quad \begin{bmatrix} y \\ z \end{bmatrix} = \begin{bmatrix} 2 \\ -1 \end{bmatrix} \quad \text{for } \lambda_1 = 0$$

$$(A - 5I)\mathbf{x} = \begin{bmatrix} -4 & 2 \\ 2 & -1 \end{bmatrix} \begin{bmatrix} y \\ z \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad \text{yields an eigenvector} \quad \begin{bmatrix} y \\ z \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \quad \text{for } \lambda_2 = 5$$

Note that these eigenvectors are *not* unique. In fact, any non-zero multiple  $c\mathbf{x}$  ( $c \neq 0$ ) of an eigenvector is another eigenvector.

Oh, and we should probably mention right now that if  $\mathbf{x} = \mathbf{0}$  then  $A\mathbf{x} = \lambda\mathbf{x}$  for *any*  $\lambda$ . So, we have to put in a qualifier that *the zero vector is never an eigenvector*. Please keep in mind that the number 0 can certainly be an eigenvalue.

# Some Facts About Eigenvectors

First, some bad news. We cannot use elimination to calculate eigenvalues. Sorry. If we use elimination to convert a matrix  $A$  into an upper triangular matrix  $U$ , the eigenvalues of  $U$  could be different than the eigenvalues of  $A$ . However, the two will not be completely unrelated.

What relates them is the amazing fact that the determinant of a matrix is equal to the product of its eigenvalues. That is to say, if  $\lambda_1, \dots, \lambda_n$  are the eigenvalues of a matrix  $A$ , then

$$\det(A) = \lambda_1 \lambda_2 \cdots \lambda_n$$

So, because  $A$  and  $U$  have the same determinant, the product of their eigenvalues will be the same.

# Some Facts About Eigenvectors

Finally, we note that the trace of a matrix is defined as being the sum of the diagonal elements.

$$\text{trace}(A) = a_{11} + a_{22} + \cdots + a_{nn}$$

The trace of a matrix will be equal to the sum of the eigenvalues of the matrix

$$\text{trace}(A) = \lambda_1 + \lambda_2 + \cdots + \lambda_n.$$

# Diagonalizing a Matrix

**Diagonalization** Suppose the  $n$  by  $n$  matrix  $A$  has  $n$  linearly independent eigenvectors  $\mathbf{x}_1, \dots, \mathbf{x}_n$ . Put those  $\mathbf{x}_i$  into the columns of an invertible *eigenvector matrix*  $X$ . Then  $X^{-1}AX$  is the diagonal *eigenvalue matrix*  $\Lambda$ :

Eigenvector matrix  $X$   
Eigenvalue matrix  $\Lambda$

$$X^{-1}AX = \Lambda = \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix}. \quad (1)$$

The matrix  $A$  is “diagonalized.” We use capital lambda for the eigenvalue matrix, because the small  $\lambda$ ’s (the eigenvalues) are on its diagonal.

# Diagonalizing a Matrix

**Example 1** This  $A$  is triangular so its eigenvalues are on the diagonal:  $\lambda = 2$  and  $\lambda = 6$ .

Eigenvectors  
go into  $X$

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

$$\begin{bmatrix} 1 & -1 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 2 & 4 \\ 0 & 6 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} 2 & 0 \\ 0 & 6 \end{bmatrix}$$
$$X^{-1} \quad A \quad X = \Lambda$$

In other words  $A = X\Lambda X^{-1}$ . Then watch  $A^2 = X\Lambda X^{-1}X\Lambda X^{-1}$ . So  $A^2$  is  $X\Lambda^2 X^{-1}$ .

*$A^2$  has the same eigenvectors in  $X$ . It has squared eigenvalues 4 and 36 in  $\Lambda^2$ .*

# Diagonalizing a Matrix

we want to express the matrix as a product of three matrices in the form:

$$A = S\Lambda S^{-1}$$

where  $\Lambda$  is a diagonal matrix. In particular, the diagonal entries of  $\Lambda$  will be the eigenvalues of  $A$ , and the columns of  $S$  will be the corresponding eigenvectors. Having  $A$  in this form can greatly simplify many calculations, particularly calculations involving powers of  $A$ .

# Diagonalizing a Matrix

$$AX = X\Lambda \quad \text{is} \quad X^{-1}AX = \Lambda \quad \text{or} \quad A = X\Lambda X^{-1}. \quad (2)$$

The matrix  $X$  has an inverse, because its columns (the eigenvectors of  $A$ ) were assumed to be linearly independent. *Without  $n$  independent eigenvectors, we can't diagonalize  $A$ .*

$A$  and  $\Lambda$  have the same eigenvalues  $\lambda_1, \dots, \lambda_n$ . The eigenvectors are different. The job of the original eigenvectors  $x_1, \dots, x_n$  was to diagonalize  $A$ . Those eigenvectors in  $X$  produce  $A = X\Lambda X^{-1}$ . You will soon see their simplicity and importance and meaning. The  $k$ th power will be  $A^k = X\Lambda^k X^{-1}$  which is easy to compute using  $X^{-1}X = I$ :

$$A^k = (X\Lambda X^{-1})(X\Lambda X^{-1}) \dots (X\Lambda X^{-1}) = X\Lambda^k X^{-1}.$$



# Things to Remember

**Remark 1** Suppose the eigenvalues are  $n$  different numbers (like 2 and 6). Then it is automatic that the  $n$  eigenvectors will be independent. The eigenvector matrix  $X$  will be *invertible*. *Any matrix that has no repeated eigenvalues can be diagonalized.*

**Remark 2** *We can multiply eigenvectors by any nonzero constants.*  $A(cx) = \lambda(cx)$  is still true. In Example 1, we can divide  $\mathbf{x} = (1, 1)$  by  $\sqrt{2}$  to produce a *unit vector*.

MATLAB and virtually all other codes produce eigenvectors of length  $\|\mathbf{x}\| = 1$ .

**Remark 3** The eigenvalues in  $\Lambda$  come in the same order as the eigenvectors in  $X$ . To reverse the order of 2 and 6 in  $\Lambda$ , put the eigenvector  $(1, 1)$  before  $(1, 0)$  in  $X$ :

$$X^{-1}AX = \Lambda_{\text{new}} \quad \begin{bmatrix} 0 & 1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} 2 & 4 \\ 0 & 6 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 6 & 0 \\ 0 & 2 \end{bmatrix} = \Lambda_{\text{new}}$$

# Things to Remember

**Remark 4** (repeated warning for repeated eigenvalues) Some matrices have too few eigenvectors. *Those matrices cannot be diagonalized.* Here are two examples :

**Not diagonalizable**

$$A = \begin{bmatrix} 1 & -1 \\ 1 & -1 \end{bmatrix} \quad \text{and} \quad B = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}.$$

Their eigenvalues happen to be 0 and 0. Nothing is special about  $\lambda = 0$ , the problem is the repetition of  $\lambda$ . All eigenvectors of the first matrix are multiples of  $(1, 1)$ :

**Only one line  
of eigenvectors**

$$Ax = 0x \quad \text{means} \quad \begin{bmatrix} 1 & -1 \\ 1 & -1 \end{bmatrix} \begin{bmatrix} x \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad \text{and} \quad x = c \begin{bmatrix} 1 \\ 1 \end{bmatrix}.$$

There is no second eigenvector, so this unusual matrix  $A$  cannot be diagonalized.

Those matrices are the best examples to test any statement about eigenvectors. In many true-false questions, non-diagonalizable matrices lead to *false*.

Remember that there is no connection between invertibility and diagonalizability:

# Things to Remember

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