

More on the diagonalization problem

Before Thanksgiving we discussed the diagonalization problem as a special case of the similarity problem for matrices.

A matrix  $\mathbf{A}$  is diagonalizable if there exists a diagonal matrix  $\mathbf{D}$  and an invertible matrix  $\mathbf{P}$  such that

$$\mathbf{D} = \mathbf{P}^{-1}\mathbf{A}\mathbf{P}.$$

Two square matrices  $\mathbf{A}$  and  $\mathbf{B}$  are similar if there exists an invertible matrix  $\mathbf{P}$  such that

$$\mathbf{B} = \mathbf{P}^{-1}\mathbf{A}\mathbf{P}.$$

**Theorem.** Suppose that  $\mathbf{A}$  and  $\mathbf{B}$  are similar matrices. Then  $\mathbf{A}$  and  $\mathbf{B}$

1. have the same characteristic polynomial and consequently the same eigenvalues, and
2. the same geometric multiplicities for each eigenvalue.

For an arbitrary matrix  $\mathbf{A}$ , what can be said about it if it is diagonalizable?

**Example.** Consider the matrix

$$\mathbf{A} = \begin{bmatrix} 2 & 1 \\ 0 & 2 \end{bmatrix}.$$

Can it be diagonalized?

**Example.** Consider the matrix

$$\mathbf{A} = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}.$$

Can it be diagonalized?

Let's see why having a basis of eigenvectors is enough to be able to diagonalize  $\mathbf{A}$ : Suppose  $\mathbf{A}$  has  $n$  linearly independent eigenvectors

$$\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$$

and let  $\lambda_i$  be the eigenvalue that is associated to  $\mathbf{v}_i$ . (Note: The  $\lambda_i$  need not be distinct.)

Then we can diagonalize  $\mathbf{A}$  using the matrix

$$\mathbf{P} = \left[ \begin{array}{c|c|c|c} \mathbf{v}_1 & \mathbf{v}_2 & \dots & \mathbf{v}_n \end{array} \right].$$

**Example.** Let

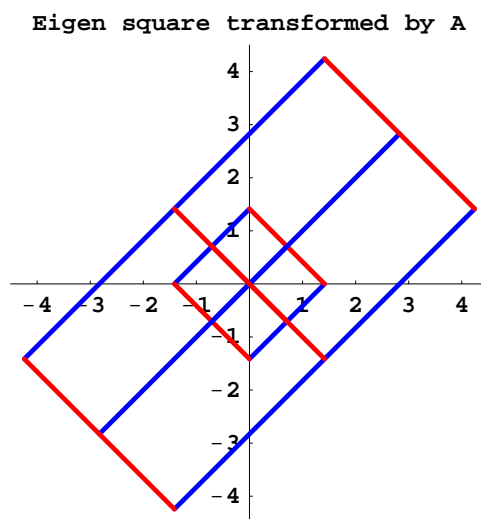
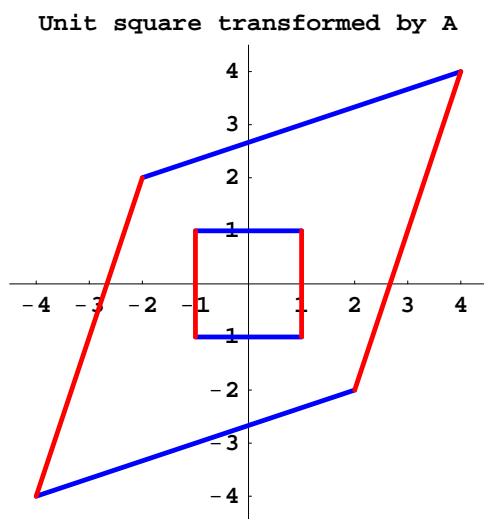
$$\mathbf{A} = \begin{bmatrix} 3 & 1 \\ 1 & 3 \end{bmatrix}.$$

We have already seen that  $\mathbf{A}$  has eigenvalues  $\lambda = 2$  and  $\lambda = 4$ . The  $\lambda = 4$  eigenspace is

$$\text{Span} \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix} \right\},$$

and the  $\lambda = 2$  eigenspace is

$$\text{Span} \left\{ \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}.$$



Now let's return to the unusual matrix that is in the animation.

**Example.** Consider the matrix

$$\mathbf{A} = \begin{bmatrix} \frac{158}{165} & \frac{19}{495} \\ \frac{38}{165} & \frac{1043}{990} \end{bmatrix}$$

The vector

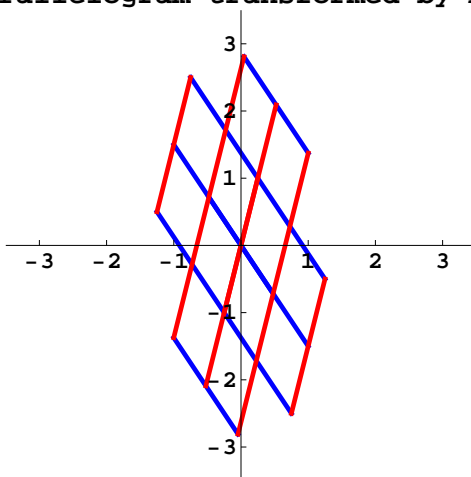
$$\begin{bmatrix} 1 \\ \frac{3}{2} \end{bmatrix}$$

is an eigenvector corresponding to the eigenvalue  $\lambda = 9/10$ , and the vector

$$\begin{bmatrix} \frac{1}{4} \\ 1 \end{bmatrix}$$

is an eigenvector corresponding to the eigenvalue  $\lambda = 10/9$ .

Parallelogram transformed by  $\mathbf{A}^7$



**Example.** Let

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

We have already seen that  $\mathbf{A}$  has eigenvalues  $\lambda = 1$  and  $\lambda = 2$ . The  $\lambda = 1$  eigenspace is the plane  $x_1 + x_2 - x_3 = 0$ , and the  $\lambda = 2$  eigenspace is the line  $x_1 = x_2 = x_3$ .

The dot product

**Definition.** Given

$$\mathbf{u} = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_n \end{bmatrix} \quad \text{and} \quad \mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_n \end{bmatrix}$$

in  $\mathbb{R}^n$ , then

$$\mathbf{u} \cdot \mathbf{v} = u_1 v_1 + u_2 v_2 + \dots + u_n v_n.$$

**Example.** Let

$$\mathbf{u} = \begin{bmatrix} 1 \\ \sqrt{2} \\ \pi \end{bmatrix} \quad \text{and} \quad \mathbf{v} = \begin{bmatrix} 5 \\ -3\sqrt{2} \\ 2 \end{bmatrix}.$$

**Remarks.**

1. The dot product  $\mathbf{u} \cdot \mathbf{v}$  can be viewed as matrix multiplication, that is,  $\mathbf{u} \cdot \mathbf{v} = \mathbf{u}^T \mathbf{v}$ .
2. Note that  $\mathbf{u} \cdot \mathbf{v} \cdot \mathbf{w}$  is undefined.
3. Note that  $(\mathbf{u} \cdot \mathbf{v}) \mathbf{w}$  involves scalar multiplication.

Let  $\mathbf{A}$  be an  $m \times n$  matrix and  $\mathbf{B}$  be an  $n \times p$  matrix. Write  $\mathbf{A}$  and  $\mathbf{B}$  as

$$\mathbf{A} = \begin{bmatrix} \mathbf{r}_1 \\ \mathbf{r}_2 \\ \vdots \\ \mathbf{r}_m \end{bmatrix} \quad \text{and} \quad \mathbf{B} = \begin{bmatrix} \mathbf{c}_1 & \mathbf{c}_2 & \dots & \mathbf{c}_p \end{bmatrix}.$$

Let's interpret the product  $\mathbf{AB}$  in terms of the dot product.

**Theorem 1.** Let  $\mathbf{u}$ ,  $\mathbf{v}$ , and  $\mathbf{w}$  be vectors in  $\mathbb{R}^n$ , and let  $c$  be a scalar. Then

- (a)  $\mathbf{u} \cdot \mathbf{v} = \mathbf{v} \cdot \mathbf{u}$
- (b)  $(\mathbf{u} + \mathbf{v}) \cdot \mathbf{w} = \mathbf{u} \cdot \mathbf{w} + \mathbf{v} \cdot \mathbf{w}$
- (c)  $(c\mathbf{u}) \cdot \mathbf{v} = c(\mathbf{u} \cdot \mathbf{v}) = \mathbf{u} \cdot (c\mathbf{v})$
- (d)  $\mathbf{u} \cdot \mathbf{u} \geq 0$ , and
- (e)  $\mathbf{u} \cdot \mathbf{u} = 0$  if and only if  $\mathbf{u} = \mathbf{0}$

**Definition.** The length (or norm) of a vector  $\mathbf{v}$  in  $\mathbb{R}^n$  is

$$\|\mathbf{v}\| = \sqrt{\mathbf{v} \cdot \mathbf{v}}.$$



Note that  $\|r\mathbf{v}\| = |r| \|\mathbf{v}\|$ .

Given  $\mathbf{v} \neq \mathbf{0}$ , we normalize  $\mathbf{v}$  by computing the vector  $\mathbf{u} = \frac{1}{\|\mathbf{v}\|} \mathbf{v}$ .

If we think of two vectors  $\mathbf{u}$  and  $\mathbf{v}$  as points in  $\mathbb{R}^n$ , then we define the distance between  $\mathbf{u}$  and  $\mathbf{v}$  as

$$\text{dist}(\mathbf{u}, \mathbf{v}) = \|\mathbf{u} - \mathbf{v}\|.$$

What about angles? Let's start with right angles.

**Definition.** Two vectors  $\mathbf{u}$  and  $\mathbf{v}$  are orthogonal if  $\mathbf{u} \cdot \mathbf{v} = 0$ .