

# Section 4.9 : Applications to Markov Chains

Chapter 4 : Vector Spaces

Math 1554 Linear Algebra

# Topics and Objectives

## Topics

We will cover these topics in this section.

1. Markov chains
2. Steady-state vectors
3. Convergence

## Objectives

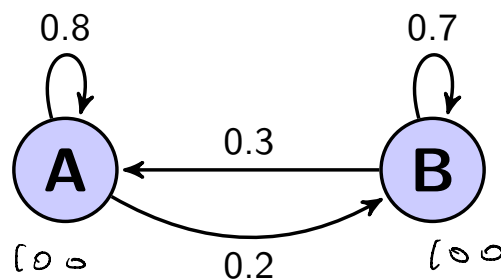
For the topics covered in this section, students are expected to be able to do the following.

1. Construct stochastic matrices and probability vectors.
2. Model and solve real-world problems using Markov chains (e.g. - find a steady-state vector for a Markov chain)
3. Determine whether a stochastic matrix is regular.

## Example 1

- A small town has two libraries,  $A$  and  $B$ .
- After 1 month, among the books checked out of  $A$ ,
  - ▶ 80% returned to  $A$
  - ▶ 20% returned to  $B$
- After 1 month, among the books checked out of  $B$ ,
  - ▶ 30% returned to  $A$
  - ▶ 70% returned to  $B$

If both libraries have 1000 books today, how many books does each library have after 1 month? After one year? After  $n$  months? A place to simulate this is <http://setosa.io/markov/index.html>



Section 4.9 Slide 3

	0	1	2	3	...	1000
A	1000	$80 + 30$				?
B	1000	$70 + 20$				?

$$0.7 \cdot (70 + 20) + 0.2 \cdot (80 + 30)$$

$$0.8 \cdot (80 + 30) + 0.3 \cdot (70 + 20)$$

		$k$	$k+1$
A	...	$x_1$	$0.8 \cdot x_1 + 0.3 \cdot x_2 = y_1$
B	...	$x_2$	$0.2x_1 + 0.7 \cdot x_2 = y_2$

$$\underbrace{\begin{bmatrix} y_1 \\ y_2 \end{bmatrix}}_{v_{k+1}} = \underbrace{\begin{bmatrix} 0.8 & 0.3 \\ 0.2 & 0.7 \end{bmatrix}}_A \underbrace{\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}}_{v_k}$$

$$v_0 = \begin{bmatrix} 100 \\ 100 \end{bmatrix}$$

$$v_1 = A v_0$$

$$v_2 = A \cdot v_1 = A \cdot (A v_0)$$

$$= A^2 \cdot v_0$$

...

$$v_{1000} = A^{1000} \cdot v_0$$

Thm  $A$  is "Nice"

No matter what vector  $v_0$  you choose

$v_N$  for large  $N$

be close to "a certain vector"

## Example 1 Continued

The books are equally divided by between the two branches, denoted by  $\vec{x}_0 = \begin{bmatrix} .5 \\ .5 \end{bmatrix}$ . What is the distribution after 1 month, call it  $\vec{x}_1$ ? After two months?

$$\vec{x}_1 = \underbrace{\begin{bmatrix} 0.8 & 0.3 \\ 0.2 & 0.7 \end{bmatrix}}_A \begin{matrix} \vec{x}_0 \\ \begin{bmatrix} .5 \\ .5 \end{bmatrix} \end{matrix} = \begin{bmatrix} 0.55 \\ 0.45 \end{bmatrix}$$

After  $k$  months, the distribution is  $\vec{x}_k$ , which is what in terms of  $\vec{x}_0$ ?

$$\vec{x}_k = A^k \cdot \begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix}.$$

# Markov Chains

$$\begin{bmatrix} 0.8 & 0.3 \\ 0.2 & 0.7 \end{bmatrix}$$

A few definitions:

- A **probability vector** is a vector,  $\vec{x}$ , with non-negative elements that sum to 1.
- A **stochastic matrix** is a square matrix,  $P$ , whose columns are probability vectors.
- A **Markov chain** is a sequence of probability vectors  $\vec{x}_k$ , and a stochastic matrix  $P$ , such that:

$$\vec{x}_{k+1} = P\vec{x}_k, \quad k = 0, 1, 2, \dots$$

- A **steady-state vector** for  $P$  is a vector  $\vec{q}$  such that  $P\vec{q} = \vec{q}$ .

## Example 2

Determine a steady-state vector for the stochastic matrix

$$\begin{pmatrix} .8 & .3 \\ .2 & .7 \end{pmatrix}$$

# Convergence

We often want to know what happens to a process,

$$\vec{x}_{k+1} = P\vec{x}_k, \quad k = 0, 1, 2, \dots$$

as  $k \rightarrow \infty$ .

**Definition:** a stochastic matrix  $P$  is **regular** if there is some  $k$  such that  $P^k$  only contains strictly positive entries.

## Theorem

If  $P$  is a regular stochastic matrix, then  $P$  has a unique steady-state vector  $\vec{q}$ , and  $\vec{x}_{k+1} = P\vec{x}_k$  converges to  $\vec{q}$  as  $k \rightarrow \infty$ .



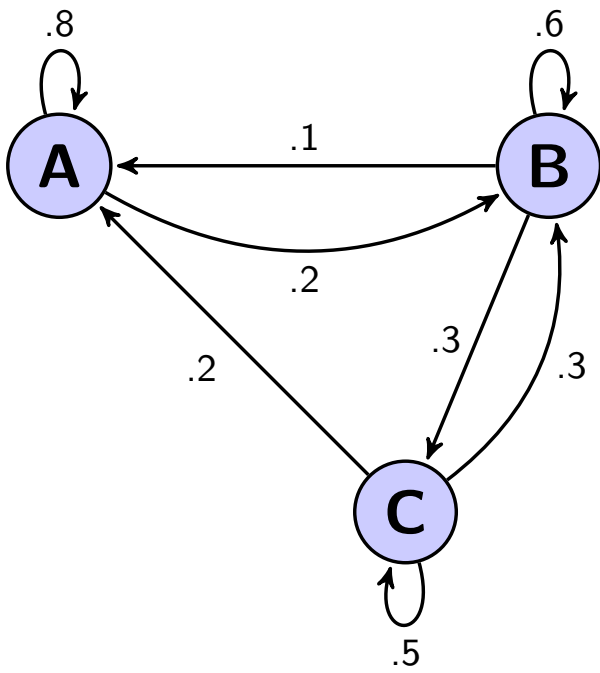
## Example 3

A car rental company has 3 rental locations, A, B, and C. Cars can be returned at any location. The table below gives the pattern of rental and returns for a given week.

		rented from		
		A	B	C
returned to	A	.8	.1	.2
	B	.2	.6	.3
	C	.0	.3	.5

There are 10 cars at each location today.

- Construct a stochastic matrix,  $P$ , for this problem.
- What happens to the distribution of cars after a long time? You may assume that  $P$  is regular.



$$P = \begin{bmatrix} .8 & .1 & .2 \\ .2 & .6 & .3 \\ .0 & .3 & .5 \end{bmatrix}$$

# Section 5.1 : Eigenvectors and Eigenvalues

Chapter 5 : Eigenvalues and Eigenvectors

Math 1554 Linear Algebra

# Topics and Objectives

## Topics

We will cover these topics in this section.

1. Eigenvectors, eigenvalues, eigenspaces
2. Eigenvalue theorems

## Objectives

For the topics covered in this section, students are expected to be able to do the following.

1. Verify that a given vector is an eigenvector of a matrix.
2. Verify that a scalar is an eigenvalue of a matrix.
3. Construct an eigenspace for a matrix.
4. Apply theorems related to eigenvalues (for example, to characterize the invertibility of a matrix).

# Eigenvectors and Eigenvalues

If  $A \in \mathbb{R}^{n \times n}$ , and there is a  $\vec{v} \neq \vec{0}$  in  $\mathbb{R}^n$ , and

$$A\vec{v} = \lambda\vec{v}$$

then  $\vec{v}$  is an **eigenvector** for  $A$ , and  $\lambda \in \mathbb{C}$  is the corresponding **eigenvalue**.

Note that

- We will only consider square matrices.
- If  $\lambda \in \mathbb{R}$ , then
  - ▶ when  $\lambda > 0$ ,  $A\vec{v}$  and  $\vec{v}$  point in the same direction
  - ▶ when  $\lambda < 0$ ,  $A\vec{v}$  and  $\vec{v}$  point in opposite directions
- Even when all entries of  $A$  and  $\vec{v}$  are real,  $\lambda$  can be complex (a rotation of the plane has no **real** eigenvalues.)
- We explore complex eigenvalues in Section 5.5.

## Example 1

Which of the following are eigenvectors of  $A = \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix}$ ? What are the corresponding eigenvalues?

a)  $\vec{v}_1 = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$

b)  $\vec{v}_2 = \begin{pmatrix} 1 \\ -1 \end{pmatrix}$

c)  $\vec{v}_3 = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$

## Example 2

Confirm that  $\lambda = 3$  is an eigenvalue of  $A = \begin{pmatrix} 2 & -4 \\ -1 & -1 \end{pmatrix}$ .

# Eigenspace

## Definition

Suppose  $A \in \mathbb{R}^{n \times n}$ . The eigenvectors for a given  $\lambda$  span a subspace of  $\mathbb{R}^n$  called the  $\lambda$ -**eigenspace** of  $A$ .

**Note:** the  $\lambda$ -eigenspace for matrix  $A$  is  $\text{Nul}(A - \lambda I)$ .

## Example 3

Construct a basis for the eigenspaces for the matrix whose eigenvalues are given, and sketch the eigenvectors.

$$\begin{pmatrix} 5 & -6 \\ 3 & -4 \end{pmatrix}, \quad \lambda = -1, 2$$



# Theorems

Proofs for the most these theorems are in Section 5.1. If time permits, we will explain or prove all/most of these theorems in lecture.

1. The diagonal elements of a triangular matrix are its eigenvalues.
2.  $A$  invertible  $\Leftrightarrow 0$  is not an eigenvalue of  $A$ .
3. Stochastic matrices have an eigenvalue equal to 1.
4. If  $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_k$  are eigenvectors that correspond to distinct eigenvalues, then  $\vec{v}_1, \vec{v}_2, \dots, \vec{v}_k$  are linearly independent.

## Warning!

We can't determine the eigenvalues of a matrix from its reduced form.

Row reductions change the eigenvalues of a matrix.

**Example:** suppose  $A = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$ . The eigenvalues are  $\lambda = 2, 0$ , because

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

- But the reduced echelon form of  $A$  is:
- The reduced echelon form is triangular, and its eigenvalues are:

# Section 5.2 : The Characteristic Equation

Chapter 5 : Eigenvalues and Eigenvectors

Math 1554 Linear Algebra

# Topics and Objectives

## Topics

We will cover these topics in this section.

1. The characteristic polynomial of a matrix
2. Algebraic and geometric multiplicity of eigenvalues
3. Similar matrices

## Objectives

For the topics covered in this section, students are expected to be able to do the following.

1. Construct the characteristic polynomial of a matrix and use it to identify eigenvalues and their multiplicities.
2. Characterize the long-term behaviour of dynamical systems using eigenvalue decompositions.

# The Characteristic Polynomial

## Recall:

$\lambda$  is an eigenvalue of  $A \Leftrightarrow (A - \lambda I)$  is not \_\_\_\_\_

Therefore, to calculate the eigenvalues of  $A$ , we can solve

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

The quantity  $\det(A - \lambda I)$  is the **characteristic polynomial** of  $A$ .

The quantity  $\det(A - \lambda I) = 0$  is the **characteristic equation** of  $A$ .

The roots of the characteristic polynomial are the \_\_\_\_\_ of  $A$ .

## Example

The characteristic polynomial of  $A = \begin{pmatrix} 5 & 2 \\ 2 & 1 \end{pmatrix}$  is:

So the eigenvalues of  $A$  are:

## Characteristic Polynomial of $2 \times 2$ Matrices

Express the characteristic equation of

$$M = \begin{pmatrix} a & b \\ c & d \end{pmatrix}$$

in terms of its determinant. What is the equation when  $M$  is singular?

# Algebraic Multiplicity

## Definition

The **algebraic multiplicity** of an eigenvalue is its multiplicity as a root of the characteristic polynomial.

## Example

Compute the algebraic multiplicities of the eigenvalues for the matrix

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



## Geometric Multiplicity

### Definition

The **geometric multiplicity** of an eigenvalue  $\lambda$  is the dimension of  $\text{Null}(A - \lambda I)$ .

1. Geometric multiplicity is always at least 1. It can be smaller than algebraic multiplicity.
2. Here is the basic example:

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

$\lambda = 0$  is the only eigenvalue. Its algebraic multiplicity is 2, but the geometric multiplicity is 1.

## Example

Give an example of a  $4 \times 4$  matrix with  $\lambda = 0$  the only eigenvalue, but the geometric multiplicity of  $\lambda = 0$  is one.

## Recall: Long-Term Behavior of Markov Chains

### Recall:

- We often want to know what happens to a Markov Chain

$$\vec{x}_{k+1} = P\vec{x}_k, \quad k = 0, 1, 2, \dots$$

as  $k \rightarrow \infty$ .

- If  $P$  is regular, then there is a \_\_\_\_\_

### Now lets ask:

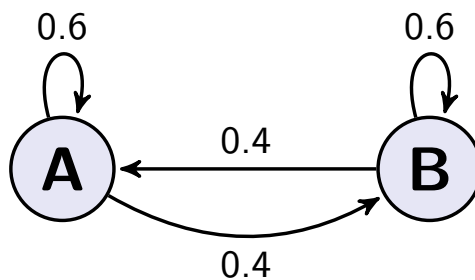
- If we don't know whether  $P$  is regular, what else might we do to describe the long-term behavior of the system?
- What can eigenvalues tell us about the behavior of these systems?

## Example: Eigenvalues and Markov Chains

Consider the Markov Chain:

$$\vec{x}_{k+1} = P\vec{x}_k = \begin{pmatrix} 0.6 & 0.4 \\ 0.4 & 0.6 \end{pmatrix} \vec{x}_k, \quad k = 0, 1, 2, 3, \dots, \quad \vec{x}_0 = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

This system can be represented schematically with two nodes, A and B:



**Goal:** use eigenvalues to describe the long-term behavior of our system.

What are the eigenvalues of  $P$ ?

What are the corresponding eigenvectors of  $P$ ?

Use the eigenvalues and eigenvectors of  $P$  to analyze the long-term behaviour of the system. In other words, determine what  $\vec{x}_k$  tends to as  $k \rightarrow \infty$ .

## Similar Matrices

### Definition

Two  $n \times n$  matrices  $A$  and  $B$  are **similar** if there is a matrix  $P$  so that  $A = PBP^{-1}$ .

### Theorem

If  $A$  and  $B$  similar, then they have the same characteristic polynomial.

If time permits, we will explain or prove this theorem in lecture. Note:

- Our textbook introduces similar matrices in Section 5.2, but doesn't have exercises on this concept until 5.3.
- Two matrices,  $A$  and  $B$ , do not need to be similar to have the same eigenvalues. For example,

$$\begin{pmatrix} 0 & 1 \\ 0 & 0 \end{pmatrix} \quad \text{and} \quad \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}$$

## Additional Examples (if time permits)

1. True or false.
  - a) If  $A$  is similar to the identity matrix, then  $A$  is equal to the identity matrix.
  - b) A row replacement operation on a matrix does not change its eigenvalues.
2. For what values of  $k$  does the matrix have one real eigenvalue with algebraic multiplicity 2?

$$\begin{pmatrix} -3 & k \\ 2 & -6 \end{pmatrix}$$