## Introduction to Markov chains

Professor: Dr. Daniel López Aguayo dlopez.aguayo@tec.mx

#### Introduction

Markov chains are named after Andrei Markov (Russian mathematician). The idea is to deal with sequences of events based on the probabilities that dictate the motion of a population among different states.

- **I** A Markov chain is a stochastic model which models sequential data.
- 2 Composed of a transition scheme between states.
- **Goals**: learn statistics, do prediction or estimation, recognize patterns.

Definition (Markov chain). A **Markov chain** is a series of discrete time intervals over which a population at a given time (say t=n) can be calculated based on the distribution at an earlier time (n-1) and the probabilities that model the population changes.

These probabilities are called **transition probabilities** and are assumed to be **constants**.

The next state depends only on the present state and not on the past history of the process.

## Features of a Markov matrix

A matrix  $T = [t_{ij}]_{,i,j=1...,n}$ , called a **transition or Markov matrix**, describes the probabilistic motion of a population between various states. A Markov matrix has several **features**.

- 1 It is square matrix (all possible states must be used).
- 2 All entries lie in [0,1] (they represent probabilities!).
- The sum of all the elements of every column must be 1 (formally:  $\sum_{i=1}^n t_{ij} = 1$  for each  $j = 1, \dots, n$ )

## Example 1. The matrix

$$A = \begin{bmatrix} 1/2 & 1/3 \\ 1/2 & 2/3 \end{bmatrix}$$

is a Markov matrix.

#### Example 2. Is

$$B = \begin{bmatrix} 1/2 & 1/3 \\ 1/5 & 2/3 \end{bmatrix}$$

a Markov matrix?

The population proportion, in its various states, is given by a column vector

$$p = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{bmatrix}$$

As you figured out in the opening activity, if we applied

$$T = \begin{bmatrix} .7 & .2 \\ .3 & .8 \end{bmatrix}$$

to a population vector such as

$$p = \begin{bmatrix} 120 \\ 80 \end{bmatrix}$$

we obtained the population distribution at the next month. More generally, we saw that

 $T^n p$  gives the population distribution after *n*th months

More generally,

Suppose a Markov chain has initial probability vector

$$p = \begin{bmatrix} p_1 \\ p_2 \\ \vdots \\ p_n \end{bmatrix}$$

and transition matrix T. The probability vector after n repetitions of the experiment is  $T^n p$ .

Question. Is there any long-range prediction? More formally, given any probability vector p, does

$$\lim_{n\to\infty} P^n p$$

exist?

**Yes.** Such result is one of the main applications of Markov chains: find long-range predictions.

**Theorem**. Let T be a Markov matrix, then for any probability vector p and for large enough n,  $T^n p$  is constant. Formally,  $\lim_{n\to\infty} T^n p$  exists.

The constant value of  $\lim_{n\to\infty}T^np$  is called the **equilibrium vector** or the **fixed vector** of the Markov chain.

In our example, the equilibrium vector associated to T was

How can we find the fixed vector? It can be shown that if  $\lim_{n\to\infty} T^n p$  exists, say V, then TV=V. Then

$$V = TV$$

$$V - TV = 0$$

$$(I - T)V = 0$$

Remark. The last equation means that we must take the matrix I-T and solve the homogeneous system (I-T)V=0. In other words, we apply **Gaussian-Jordan elimination** to the augmented matrix [I-T|0].

# An example

Example. Consider the example from the opening activity, in this case the Markov matrix is given by

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

Step 1 Build the augmented matrix [I - T|0]:

$$\left[\begin{array}{cc|c} 1 - 0.7 & 0 - 0.2 & 0 \\ 0 - 0.3 & 1 - 0.8 & 0 \end{array}\right]$$

$$\left[ \begin{array}{cc|c}
0.3 & -0.2 & 0 \\
-0.3 & 0.2 & 0
\end{array} \right]$$

Finally, row reduction yields

$$\left[\begin{array}{cc|c} 0.3 & -0.2 & 0 \\ 0 & 0 & 0 \end{array}\right]$$

Step 2 Solve the system. The first equation gives 0.3x - 0.2y = 0. In our case,

$$x + y = 200$$
, so  $0.3x - 0.2(200 - x) = 0$ ; therefore  $(x, y) = (80, 120)$