

# Introduction to Hidden Markov Models (HMMs)

Dr. Vianey Leos Barajas -- University of Toronto

Sofia Ruiz Suarez -- INIBIOMA-CONICET/Universidad Nacional de Rosario



RIIAA

MEETING ON ARTIFICIAL INTELLIGENCE AND ITS APPLICATIONS

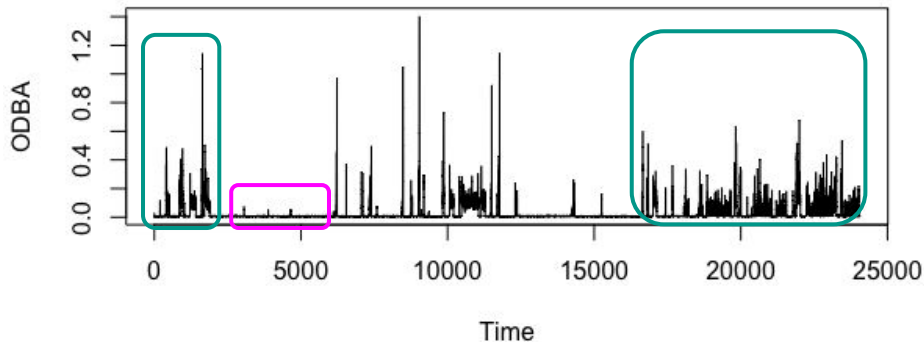
25-27 August 2021

# Hidden Markov Models for Time Series

A **hidden Markov model (HMM)** is used to model data collected over time (or in sequence) where we can make two key assumptions:

- a set of  $N$  different patterns manifest in the data
- there is persistence in the pattern over time (or sequence)

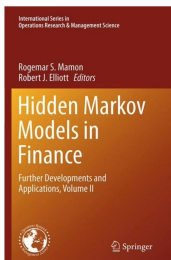
**Example:**



# Where have HMMs been used?

## Finance

market regimes



## Medicine

disease progression

## Ecology

animal movement

capture recapture

## General Pattern Recognition

speech recognition

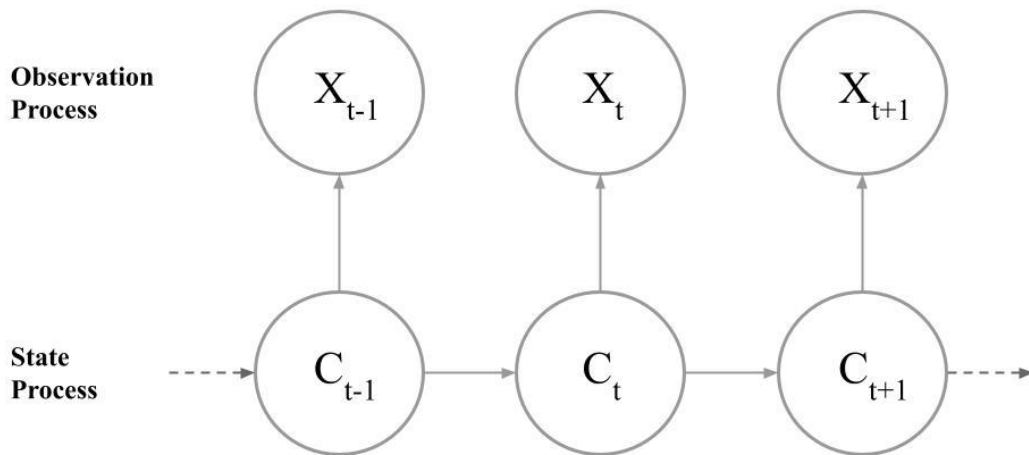
human movement

# Hidden Markov Models (HMMs)

**HMMs:** A doubly stochastic process composed of an

**observation process:**  $X_{t=1}^T$  and a **state process:**  $C_{t=1}^T$

where the state process  $C_{t=1}^T$  is taken to be a Markov chain



# Data Types: *Observations* + *States*

$X_{t=1}^T$  can be:

- univariate
- multivariate
- continuous
- discrete
- measured with error

$C_{t=1}^T$  is taken to be:

- integer-valued (1, 2, 3,...)

**Discrete-time HMM:**  $X_{t=1}^T$  is assumed to be observed regularly over time

**Finite-state HMM:**  $C_{t=1}^T$  can take on a finite set of integer values

# Components of an HMM

A basic (discrete-time, finite-state) HMM is fully specified by 4 components:

Mathematical Description:

Number of states:

$$N \in \mathbb{N}$$

State-dependent distributions:

$$\{f(X_t|C_t = n)\}_{n=1}^N$$

Transition probability matrix (t.p.m.):

$$\Gamma_{i,j} = \Pr(C_t = j|C_{t-1} = i) \quad \text{for } i, j \in \{1, \dots, N\}$$

Initial state distribution:

$$\delta_i = \Pr(C_1 = i) \quad \text{for } i \in \{1, \dots, N\}$$

# Components of an HMM (cont.)

## General Interpretation

### Number of states

Translation: Number of patterns

### State-dependent distributions:

Translation: Distribution of observations within each pattern

### Transition probability matrix

Translation: How the patterns evolve over time

### Initial state distribution

Translation: What pattern occurred at the first time point?

# State dwell time distribution

As the state process is taken to be a Markov chain, that means that there is an expected amount of time a state will 'last' until it switches to another state process over time.

$$d_n \sim \textit{Geometric}(1 - \Gamma_{nn})$$

The expected number of times that a state will be exhibited over time before there is a switch is  $E(d_n) = 1/(1 - \Gamma_{nn})$



# Example

Number of states:  $N = 3$

State-dependent distributions:

$$f(X_t | C_t = n) \sim N(\mu_n, \sigma_n) \quad \text{for } n \in \{1, 2, \dots, N\}$$

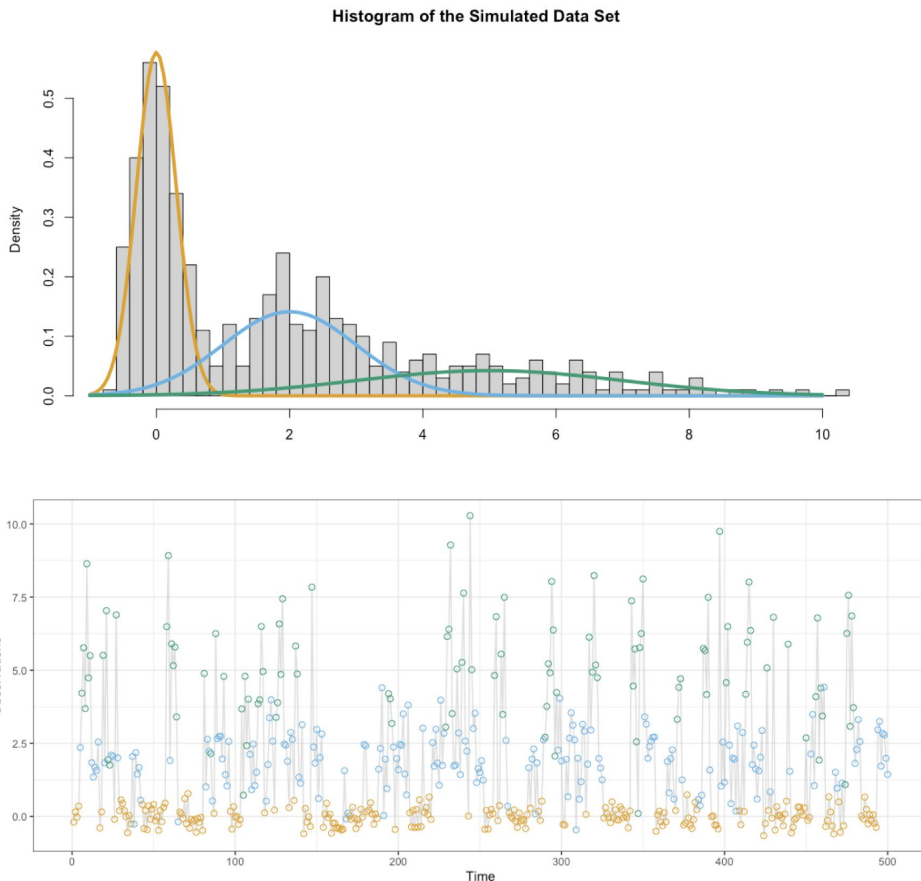
$$\{\mu_1 = 0, \sigma_1 = 0.3\} \{\mu_2 = 2, \sigma_2 = 1\} \{\mu_3 = 5, \sigma_3 = 2\}$$

Transition probability matrix:

$$\mathbf{\Gamma} = \begin{bmatrix} .8 & 0.1 & 0.1 \\ 0.2 & 0.7 & 0.1 \\ 0.05 & 0.35 & 0.6 \end{bmatrix}$$

Initial state distribution:

$$\boldsymbol{\delta} = [1/3, 1/3, 1/3]$$



# How to simulate data from an N-state HMM

1. Sample  $C_1$  from the initial state distribution  $\delta$
2. Given  $C_1 = i_1$ , sample  $C_2$  using  $\mathbf{\Gamma}_{i_1}$ .
3. Repeat step 2 for  $C_3, \dots, C_T$
4. Given  $\{C_1 = i_1, C_2 = i_2, \dots, C_T = i_T\}$ , for  $t = 1, \dots, T$  simulate from  $f(X_t | C_t = i_t)$

# Simulation in R