1. what is HMM? Book Ch.1-2
2. what is accelerometer data? Paper

HMM

Chapter 1: Preliminaries – Mixtures and Markov Chains

Mixture Models:
Mixtures arise when observations come from several underlying distributions, with the choice of component governed by a random mechanism. For example, a Poisson mixture can capture overdispersed count data (e.g., earthquake counts). Independent mixtures explain heterogeneity but assume no serial dependence.

Markov Chains:
A Markov chain is a sequence of random states where the future depends only on the present state (memoryless property). Key ideas include transition probabilities, stationary distributions, and higher-order chains.

Motivation for HMMs:
Standard models like ARMA may fail for discrete or overdispersed series. Mixtures help but miss temporal dependence. Markov chains capture dependence but not observation variability. HMMs combine both ideas

Chapter 2: Hidden Markov Models – Definition and Properties

Basic Structure:
An HMM consists of two linked processes:

A hidden Markov chain of states that evolves over time.

An observation process where each observation is generated according to a distribution determined by the current hidden state.

Key Properties:

Observations are conditionally independent given the hidden states.

The marginal distribution of observations is a dependent mixture, unlike the independent mixtures in Chapter 1.

HMMs can capture serial dependence in observed data while still being tractable.

Likelihood:
The likelihood of observed data under an HMM can be computed efficiently (via forward algorithms). Unlike pure Markov chains, the observed sequence alone is not Markovian

An HMM is a time series model where the data are driven by an unobserved Markov chain. Each hidden state corresponds to a different distribution for the observations. By combining mixture distributions (for heterogeneity) with Markov chains (for temporal dependence), HMMs provide a flexible and powerful framework for modeling complex time series.

Accelerometer Data
measurements collected by accelerometer
record acceleration along one, two, or three axes relative to the body of the animal:
Longitudinal (surge): forward-backward movements
Lateral (sway): side-to-side movements
Dorsoventral (heave): up-down movements

Key Points:
What it Measures:
Accelerometers capture how the body (or part of the body) moves over time, producing high-resolution time series data. This includes both static acceleration (due to gravity, linked to body posture) and dynamic acceleration (due to movement, like running or flapping).

Applications:
In animal ecology, accelerometer data help infer behaviour (e.g., foraging, resting, flying, or swimming) when direct observation is impossible
In humans, it’s used for activity recognition (walking, running, sitting) and health monitoring.

Derived Metrics:
To interpret raw accelerometer signals, researchers often calculate metrics such as:
Overall Dynamic Body Acceleration (ODBA): a proxy for energy expenditure.
Minimum Specific Acceleration (MSA): separates gravitational (static) and movement (dynamic) components.
Means and variances of each axis over short windows (used for classification tasks).

Why It’s Useful:
Accelerometer data provide a quantitative, continuous record of movement and activity that can be linked to behaviours, energy use, or environmental drivers. For example, repeating patterns may indicate flapping or running, while sudden bursts in acceleration often reflect prey capture or predator evasion.