

## 1 Basic Markov Chains

**Definition 1.** A sequence of random variables  $X_1, X_2, \dots$  taking values in a state space  $S$  is a **Markov chain** if it satisfies the Markov property  $\forall t$ :

$$\mathbb{P}(X_t = x_t | X_1 = x_1, \dots, X_{t-1} = x_{t-1}) = \mathbb{P}(X_t = x_t | X_{t-1} = x_{t-1}).$$

That is, the value of  $X_t$  depends **only** on the value of  $X_{t-1}$ .

**Definition 2.** A Markov chain  $X_1, X_2, \dots$  is **time homogeneous** iff the transition probabilities don't depend on  $t$ :

$$\mathbb{P}(X_t = j | X_{t-1} = i) = \mathbb{P}(X_{t'} = j | X_{t'-1} = i) \quad \forall t, t'.$$

## 2 Hidden Markov Models

**Definition 3.** A **hidden Markov Model** involves an unobservable Markov chain  $X_1, X_2, \dots$  and a sequence of observations  $Y_1, Y_2, \dots$  each from an observation space  $O = \{o_1, \dots, o_M\}$  such that:

$$\mathbb{P}(Y_t = y_t | X_1 = x_1, \dots, X_t = x_t, Y_1 = y_1, \dots, Y_{t-1} = y_{t-1}, Y_{t+1} = y_{t+1}, \dots) = \mathbb{P}(Y_t = y_t | X_t = x_t).$$

That is,  $Y_t$  depends **only** on  $X_t$ .

An HHM with hidden state space  $S = [N]$  and  $M$  possible observations can be parameterised fully as  $\lambda = (\pi, A, B)$  where:

- $\pi \in \mathbb{R}^N$  is the **initial distribution** over state space  $S$ :

$$\pi_i = \mathbb{P}(X_1 = i).$$

- $A \in \mathbb{R}^{N \times N}$  gives us the **transition probabilities**:

$$a_{ij} = \mathbb{P}(X_t = j | X_{t-1} = i).$$

- $B = \{b_j(o_k) : j \in [N], k \in [M]\}$  gives us the **emission/observation probabilities**:

$$b_j(o_k) = \mathbb{P}(Y_t = o_k | X_t = j).$$

The mini-lecture will focus on **filtering**, **smoothing** and **parameter estimation**. In the discussion of these topics we will be using the following quantities:

- Forward probabilities:

$$\alpha_t(i) = \mathbb{P}(Y_1, \dots, Y_t, X_t = i | \lambda)$$

- Backward probabilities:

$$\beta_t(i) = \mathbb{P}(Y_{t+1}, \dots, Y_T | X_t = i, \lambda)$$

- Smoothed probabilities

$$\gamma_t(i) = \mathbb{P}(X_t = i | Y, \lambda) = \frac{\alpha_t(i)\beta_t(i)}{\sum_{j=1}^N \alpha_t(j)\beta_t(j)}$$

- Discussion of parameter estimation via the Baum-Welch algorithm will also require the following probability:

$$\xi_t(i, j) = \mathbb{P}(X_t = i, X_{t+1} = j | Y, \lambda)$$