

Markov Model and Markov Property

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Learning Objectives

- ❑ To understand the concept of independence in probability
- ❑ To familiarize the Markov model and Markov property
- ❑ To familiarize Chapman-Kolmogorov equation

Independence

- ❑ One of the most important concepts defined in probability theory is independence.
- ❑ The concept of independence is essential to decompose a complex problem into simpler and manageable components.
- ❑ Markov models rely on assumptions of independence.

Definition of Independence

□ **Definition 3.1** (*Conditional Independence*). For $A, B, C \in \mathcal{A}$, A is said to be *conditionally independent* with B on C if and only if

For $A, B, C \in \mathcal{A}$, A is said to be conditionally independent with B on C if and only if

$$p(A \cap B | C) = p(A | C)p(B | C).$$

□ **Definition 3.2** (*Independence*). For $A, B \in \mathcal{A}$, A is said to be *independent* with B if and only if

A is said to be independent with B if and only if

$$p(A \cap B) = p(A)p(B).$$

Independence can be seen as a special case of Conditional Independence where $C = \Omega$.

Knowledge Accumulation

□ **Lemma 3.1.** For $A, B, C \in \mathcal{A}$,

$$p(A \cap B | C) = p(A | B \cap C) p(B | C)$$

Proof.

$$\begin{aligned} p(A \cap B | C) &= p(A \cap B \cap C) / p(C) \\ &= p(A | B \cap C) p(B \cap C) / p(C) \\ &= p(A | B \cap C) p(B | C) \end{aligned}$$

Equivalent Views of Independence

□ **Theorem 3.2.** For $A, B, C \in \mathcal{A}$,

$$p(A \cap B | C) = p(A | C)p(B | C) \Leftrightarrow p(A | B \cap C) = p(A | C)$$

Proof.

$$p(A \cap B | C) = p(A | B \cap C)p(B | C) = p(A | C)p(B | C)$$

$$\Leftrightarrow p(A | B \cap C) = p(A | C)$$

Graphoid Properties

- The most intuitive meaning of ‘independence’ is that an independence relationship satisfies several *graphoid* properties.
- With X, Y, Z, W as sets of disjoint random variables and “ \perp ” denoting independence and “ $|$ ” as condition, the axioms of graphoid are:
 - (A1) Symmetry
 - (A2) Decomposition
 - (A3) Weak union
 - (A4) Contraction
 - (A5) Intersection

Graphoid - Symmetry

$$X \perp Y \mid Z \Rightarrow Y \perp X \mid Z$$

- **Remark 3.1.** If knowing Y does not tell us more about X , then similarly knowing X does not tell us more about Y .

Graphoid - Decomposition

$$X \perp (W, Y) \mid Z \Rightarrow X \perp Y \mid Z$$

- **Remark 3.2.** If combined two pieces of information is irrelevant to X , either individual one is also irrelevant to X .

Graphoid - Weak Union

$$X \perp (W, Y) \mid Z \Rightarrow X \perp W \mid (Y, Z)$$

- **Remark 3.3.** Gaining more information about irrelevant Y does not affect the irrelevance between X and W .

Graphoid - Contraction

$$(X \perp Y \mid Z) \wedge (X \perp W \mid (Y, Z)) \Rightarrow X \perp (W, Y) \mid Z$$

□ **Remark 3.4.** If two pieces of information X and Y are irrelevant with prior knowledge of Z and X is also irrelevant to a third piece of information W after knowing Y , then X is irrelevant to both W and Y before knowing Y .

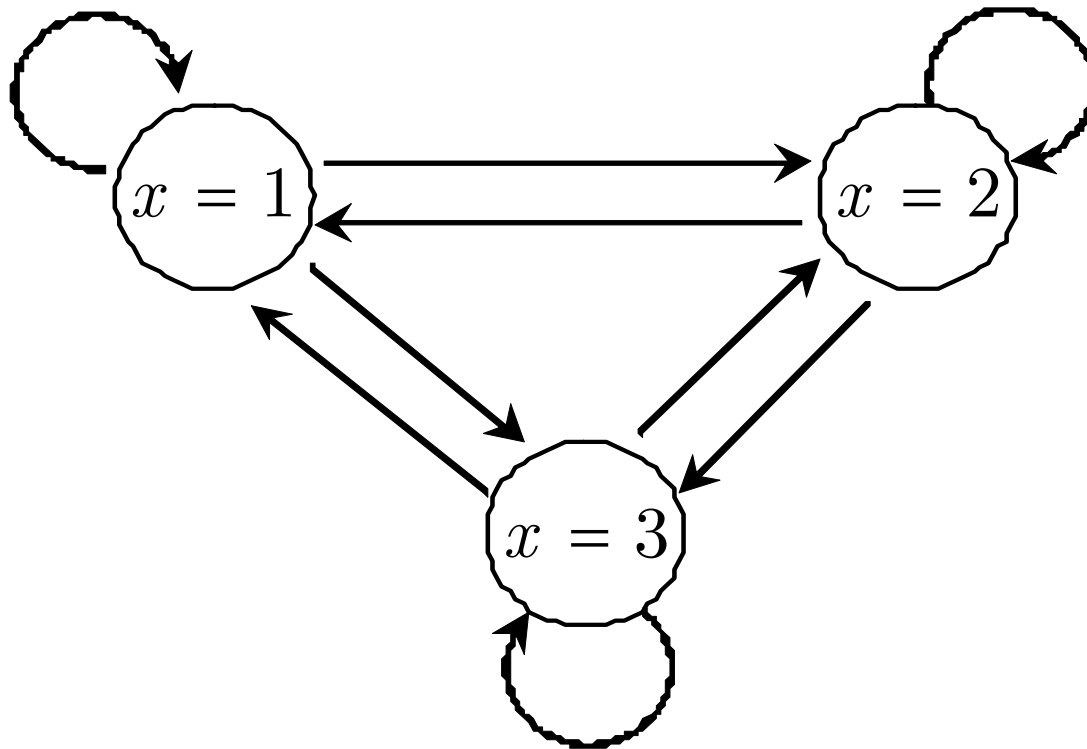
Graphoid - Intersection

$$\left(X \perp W \mid (Y, Z) \right) \wedge \left(X \perp Y \mid (W, Z) \right) \Rightarrow X \perp (W, Y) \mid Z$$

- **Remark 3.5.** If combined information W and Y is relevant to X , then at least either W or Y is relevant to X after learning the other.

Discrete-Time Markov Chain

□ State transition diagram

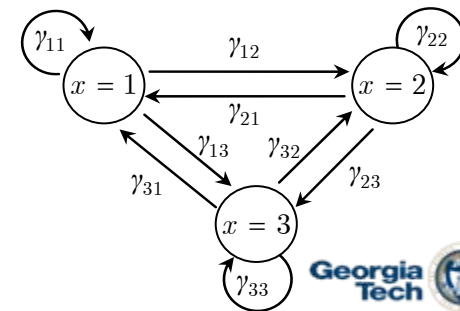


Markov Property

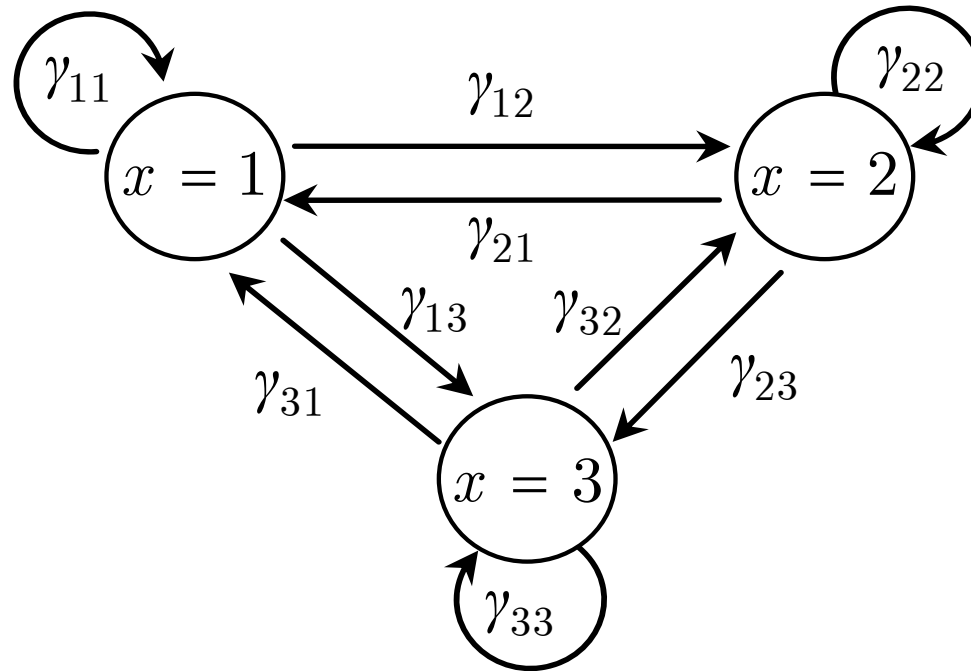
- A Markov chain represents a Markov process of state transitions, where the “memoryless” Markov property is assumed.

$$P\left(x^{(t+1)} \mid x^{(t)}, \dots, x^{(0)}\right) = P\left(x^{(t+1)} \mid x^{(t)}\right)$$

- Loosely speaking, the future state of a random variable $x^{(t+1)}$ at time $t+1$ only depends on its current state $x^{(t)}$, not the complete transition history.



Transition Probability

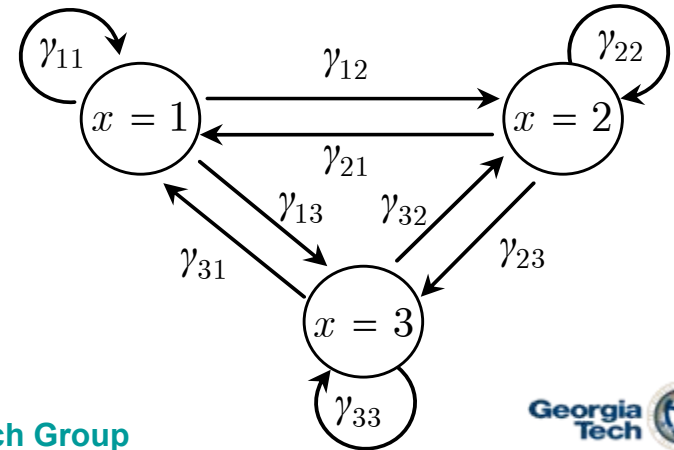


$$P\left(x^{(t+1)} = j \mid x^{(t)} = i\right) = \gamma_{ij} \quad (i, j = 1, 2, 3)$$

Transition Matrix

$$\Gamma = \left(\gamma_{ij} \right)_{3 \times 3} = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} \end{bmatrix}$$

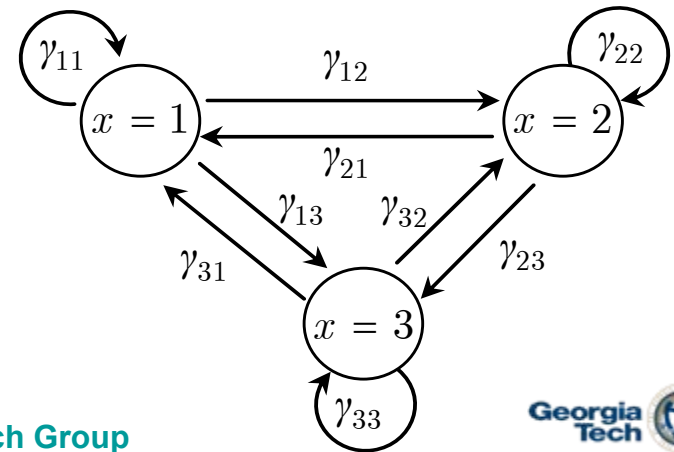
where $\sum_{j=1}^3 \gamma_{ij} = 1 \quad (i = 1, 2, 3)$



State Vector

$$\Delta^{(t)} = \left(\delta_1^{(t)}, \delta_2^{(t)}, \delta_3^{(t)} \right)$$

where $P(x^{(t)} = i) = \delta_i$ ($i = 1, 2, 3$)



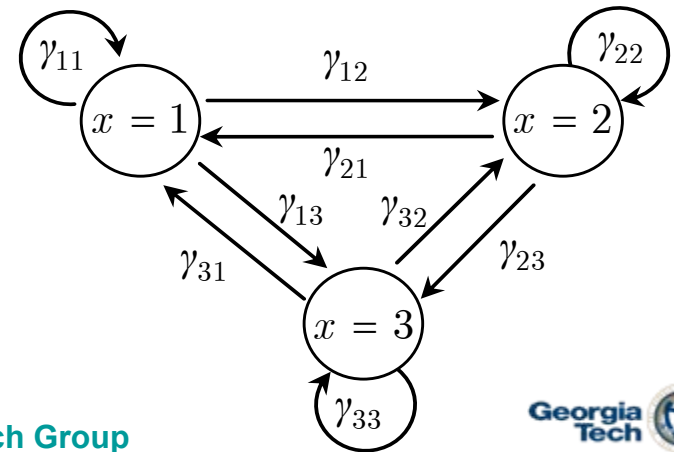
State Transition

□ State update

$$\Delta^{(t+1)} = \Delta^{(t)}\Gamma$$

□ Stationary distribution

$$\Delta = \Delta\Gamma$$



Extensions of Discrete-Time Markov Chain

- ❑ When the transition matrix $\Gamma^{(t)}$ is not constant, it is called a *non-homogeneous Markov chain*.
- ❑ When the time is not discrete, it is called *continuous-time Markov chain*.

Ergodicity

□ **Definition 3.3.** A Markov chain $\Gamma^{(t)} = \left(\gamma_{ij}^{(t)} \right)$ is called *irreducible* if for all states $x \in \Omega$, there exists a time t such that $\gamma_{ij}^{(t)} > 0$ ($\forall i, j$)

“every state is eventually reachable”

□ **Definition 3.4.** A Markov chain $\Gamma^{(t)} = \left(\gamma_{ij}^{(t)} \right)$ is called *aperiodic* if for all states $x \in \Omega$,
$$\gcd \left\{ t : \gamma_{ij}^t > 0 \right\} = 1 \quad .$$

“it doesn't get caught in cycles”

□ **Definition 3.5.** A Markov chain is called *ergodic* if it is both irreducible and aperiodic.

Chapman-Kolmogorov Equation

□ Suppose there are a total of K states

$$\begin{aligned} & P\left(x^{(t+s)} = j \mid x^{(0)} = i\right) \\ &= \sum_{k=1}^K P\left(x^{(t+s)} = j \mid x^{(s)} = k\right) P\left(x^{(s)} = k \mid x^{(0)} = i\right) \end{aligned}$$

Forward Differential Kolmogorov Equation

□ For a small time step h

$$\begin{aligned} & P\left(x^{(t+h)} = j \mid x^{(0)} = i\right) \\ &= \sum_{k=1}^K P\left(x^{(t+h)} = j \mid x^{(t)} = k\right) P\left(x^{(t)} = k \mid x^{(0)} = i\right) \\ &= \sum_{k \neq j} P\left(x^{(t+h)} = j \mid x^{(t)} = k\right) P\left(x^{(t)} = k \mid x^{(0)} = i\right) \\ &+ P\left(x^{(t+h)} = j \mid x^{(t)} = j\right) P\left(x^{(t)} = j \mid x^{(0)} = i\right) \end{aligned}$$

Forward Differential Kolmogorov Equation

$$\begin{aligned} & P\left(x^{(t+h)} = j \mid x^{(0)} = i\right) - P\left(x^{(t)} = j \mid x^{(0)} = i\right) \\ &= \sum_{k \neq j} P\left(x^{(t+h)} = j \mid x^{(t)} = k\right) P\left(x^{(t)} = k \mid x^{(0)} = i\right) \\ &+ P\left(x^{(t)} = j \mid x^{(0)} = i\right) \left[P\left(x^{(t+h)} = j \mid x^{(t)} = j\right) - 1 \right] \\ &= \sum_{k \neq j} P\left(x^{(t+h)} = j \mid x^{(t)} = k\right) P\left(x^{(t)} = k \mid x^{(0)} = i\right) \\ &- P\left(x^{(t)} = j \mid x^{(0)} = i\right) \sum_{k \neq j} P\left(x^{(t+h)} = k \mid x^{(t)} = j\right) \end{aligned}$$

Forward Differential Kolmogorov Equation

$$\begin{aligned} & P\left(x^{(t+h)} = j \mid x^{(0)} = i\right) - P\left(x^{(t)} = j \mid x^{(0)} = i\right) \\ &= \sum_{k \neq j} \left[\begin{aligned} & P\left(x^{(t+h)} = j \mid x^{(t)} = k\right) P\left(x^{(t)} = k \mid x^{(0)} = i\right) \\ & - P\left(x^{(t+h)} = k \mid x^{(t)} = j\right) P\left(x^{(t)} = j \mid x^{(0)} = i\right) \end{aligned} \right] \end{aligned}$$

Then we have

$$\begin{aligned} & \left[P\left(x^{(t+h)} = j \mid x^{(0)} = i\right) - P\left(x^{(t)} = j \mid x^{(0)} = i\right) \right] / h \\ &= \sum_{k \neq j} \left[\begin{aligned} & P\left(x^{(t)} = k \mid x^{(0)} = i\right) P\left(x^{(t+h)} = j \mid x^{(t)} = k\right) / h \\ & - P\left(x^{(t)} = j \mid x^{(0)} = i\right) P\left(x^{(t+h)} = k \mid x^{(t)} = j\right) / h \end{aligned} \right] \end{aligned}$$

Forward Differential Kolmogorov Equation

□ Define the jump rate as

$$q_{k \leftarrow j}^{(t)} = P \left(x^{(t+h)} = k \mid x^{(t)} = j \right) / h \quad (j \neq k)$$

□ Then

$$\begin{aligned} & P \left(x^{(t)} = j \mid x^{(0)} = i \right) \\ &= \sum_{k \neq j} \left[\begin{array}{c} q_{j \leftarrow k}^{(t)} P \left(x^{(t)} = k \mid x^{(0)} = i \right) \\ - q_{k \leftarrow j}^{(t)} P \left(x^{(t)} = j \mid x^{(0)} = i \right) \end{array} \right] \end{aligned}$$

Summary

- Independence is one of the essential properties in probability calculus
- “Memoryless” Markov property simplifies inference in state transition

Memoryless