

SNS COLLEGE OF TECHNOLOGY

Coimbatore-35
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DEPARTMENT OF ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

23AMB201 - MACHINE LEARNING

II YEAR IV SEM

UNIT V – Reinforcement Learning TEMPORAL MODEL

Temporal Model/S.Rajarajeswari/AP/AIML/SNSCT/



UNCERTAIN KNOWLEDGE AND REASONING

- Uncertainty
- Review of probability
- Probabilistic Reasoning
- Bayesian networks
- Inferences in Bayesian networks
- Temporal models
- Hidden Markov models





Temporal Models

- Two sections in Temporal Model,
 - Time and Uncertainty
 - States and observations
 - Stationary processes and the Markov assumption
 - Inference in Temporal Model



Temporal Models - Time and Uncertainty

- A changing world is **modeled** using a **random variable** for each aspect of the environment **state**, *at each point in time*.
- The **relations** among these variables describe how the state evolves.





Temporal Models

- Agents in uncertain environments must be able to keep track of the current state of the environment, just as logical agents must.
- This is difficult by partial and noisy data, because the environment is uncertain over time.
- At best, the agent will be able to obtain only a probabilistic assessment of the current situation.





Example - Treating a Diabetic Patient.

- We have **evidence**, such as, recent insulin doses, food intake, blood sugar measurements, and other physical signs.
- The task is **to assess** the current state of the patient, including the actual blood sugar level and insulin level.
- Given **this information**, the doctor (or patient) **makes a decision** about the patient's food intake and insulin dose.





Example - Treating a Diabetic Patient...

- The **dynamic aspects** of the problem are essential.
- Blood sugar levels and measurements thereof can **change rapidly** over time, depending on **one's recent food intake and insulin doses, one's metabolic activity, the time of day, and so on.**
- To assess the current state from the history of evidence and to predict the outcomes of treatment actions, we must model these changes.





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States and Observations

- The process of change can be viewed as a series of **snapshots** (results), describes the state of the world at a particular time.
- Each snapshot or **time slice**, contains a set of random variables, some of which are observable and some of which are not.





State and observation ...

- Example: **Umbrella and Rain**
- Suppose you are a security guard for some secret underground installation
- You want to know whether it is **raining** today
- But, your only access to the outside world occurs **each morning**, when you see the director coming in with, or without an **umbrella**.





State and observation ...

- We will assume that the same subset of variables is observable in each slice
- X_t – set of unobservable state variable at time t
- E_t – set of observable evidence variable
- The observation at time t is $E_t = e_t$ for some set of values e_t





Example: Umbrella and Rain...

- For each day t , the set E_t (observable evidence variables) thus contains a single evidence variable U_t (whether the umbrella appears) and the set X_t (unobservable state variable) contains a single state variable R_t (whether raining or not)
- Hence we can assume $E_t = U_t$ and $X_t = R_t$
- And if $E_t = \text{true}$ then $X_t = \text{true}$
- i.e. if $U_t = \text{true}$ then $R_t = \text{true}$





State and observation ...

- The interval between **time slices** also depends on the problem.
- For diabetes monitoring, a suitable interval might be an hour rather than a day.
- We generally assume a fixed, finite interval; this means that **times can be labeled by integers**.
- We will assume that evidence starts arriving at **$t = 1$** rather than $t = 0$.
- Hence, our umbrella world is represented by **state variables** **R_0** will be, R_1, R_2, \dots and **evidence variables** U_1, U_2, \dots .
- We will use the notation **$a:b$** to denote the sequence of integers from **a** to **b** and the notation $X_{a:b}$ to denote the corresponding set of variables from X_a to X_b .
- For example, $U_{1:3}$ corresponds to the variables U_1, U_2, U_3 .





Redesigning Common Mind & Business Towards Excellence



Build an Entrepreneurial Mindset Through Our Design Thinking FrameWork

- Two section in Temporal Model:
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 - * Stationary process and the Markow assumption
 - * Inference in Temporal Model



Stationary Processes and the Markov assumption

- With the set of **state and evidence variables** for a given problem, we need to specify the **dependencies among the variables**.
- Order the variables in their natural temporal order
- Since **cause usually precedes effect** so we need to add the variables in causal order.





Stationary Processes and the Markov assumption...

- Solution for the problems
- The **first problem** is solved by assuming that changes in the world state are caused by a **stationary process**-that is, a process of change that is governed by laws that do not themselves change over time.
- In the umbrella world, the conditional probability that the umbrella appears, $P(U_t \mid \text{Parents}(U_t))$, is the same for all t .





Stationary Processes and the Markov assumption...

- The set of variables is **unbounded**, because it includes the state and evidence variables for every time slice.
- This actually creates **two problems**:
 - **first**, we might have to specify an unbounded number of **conditional probability tables (CPT)**, one for each variable in each slice;
 - **second**, each one might involve an **unbounded number of parents**.





Stationary Processes and the Markov assumption...

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Stationary Processes and the Markov assumption...

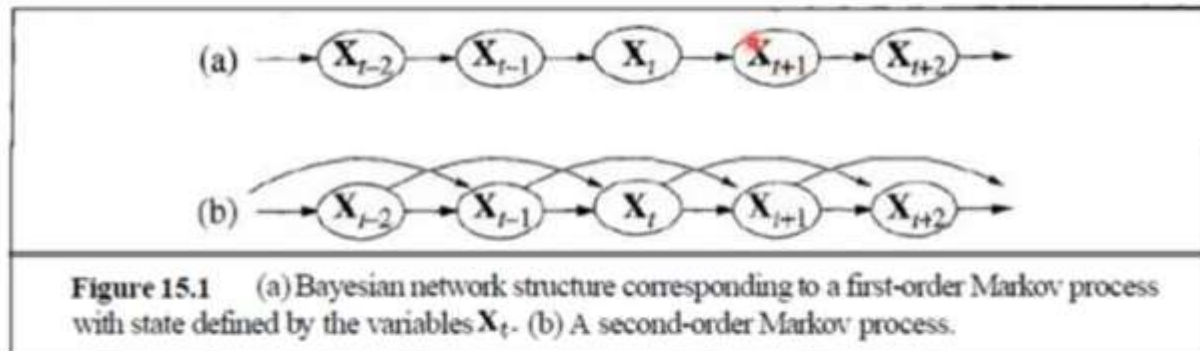
- The second problem, handling the infinite number of parents, is solved by making a **Markov assumption**-that is, that the current state depends on only a finite history of previous states.
- the simplest is the first-order **Markov process**
- in which the current state depends only on the previous state and not on any earlier states.
- Using our notation, the corresponding conditional independence assertion states that, for all t ,

$$P(X_t | X_{0:t-1}) = P(X_t | X_{t-1})$$





Stationary Processes and the Markov assumption...





Stationary Processes and the Markov assumption...

- The transition model for a **second-order Markov process** is the conditional distribution $P(X_t \mid X_{t-2}, X_{t-1})$.
- current state depends on only two previous **states**





Stationary Processes and the Markov assumption...

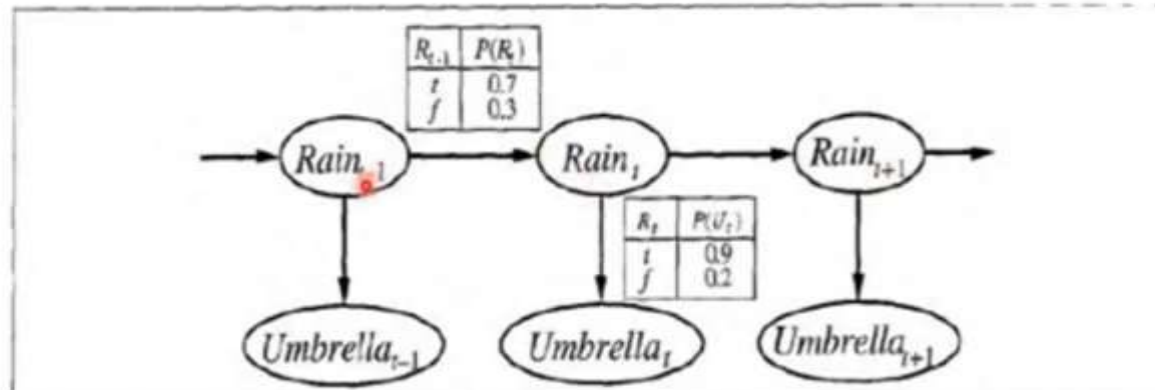


Figure 15.2 Bayesian network structure and conditional distributions describing the umbrella world. The transition model is $P(Rain_t | Rain_{t-1})$ and the sensor model is $P(Umbrella_t | Rain_t)$.

