

# Probabilistic Reasoning

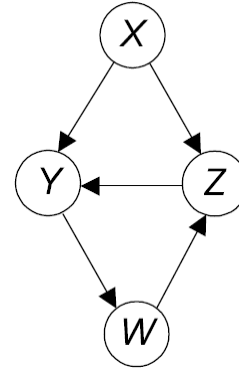
## Unit # 6

## Directed Graph

- A **directed graph** is a pair  $(V, E)$ , where  $V$  is a finite, nonempty set whose elements are called **nodes** (or vertices), and  $E$  is a set of ordered pairs of distinct elements of  $V$ .
- Elements of  $E$  are called **directed edges**, and if  $(X, Y) \in E$ , we say there is an edge from  $X$  to  $Y$ .

## Directed Graph (Cont'd)

- $V = \{X, Y, Z, W\}$
- $E = \{(X, Y), (X, Z), (Z, Y), (Y, W), (W, Z)\}$



## Path and Cycle

- A **path** in a directed graph is a sequence of nodes  $[X_1, X_2, \dots, X_k]$  such that  $(X_{i-1}, X_i) \in E$  for  $2 \leq i \leq k$ .
- A **cycle** in a directed graph is a path from a node to itself.

## Directed Acyclic Graph

- A directed graph  $G$  is called a **directed acyclic graph (DAG)** if it contains no cycle.

## More Definitions

- Given a DAG  $G = (V, E)$  and nodes  $X$  and  $Y$  in  $V$ ,
  - $Y$  is called a **parent** of  $X$  if there is an edge from  $Y$  to  $X$ ,
  - $Y$  is called a **descendent** of  $X$  and  $X$  is called an **ancestor** of  $Y$  if there is a path from  $X$  to  $Y$ , and
  - $Y$  is called a **non-descendent** of  $X$  if  $Y$  is not a descendent of  $X$  and  $Y$  is not a parent of  $X$ .

## Markov Condition and Bayesian Network

- Suppose we have a joint probability distribution  $P$  of the random variables in some set  $V$  and a DAG  $G = (V, E)$ .
- We say that  $(G, P)$  satisfies the **Markov condition** if for each variable  $X \in V$ ,  $X$  is conditionally independent of the set of all of its non-descendants (ND) given the set of all its parents (PA).
- If  $(G, P)$  satisfies the Markov condition, we call  $(G, P)$  a **Bayesian network**.

## Theorem

- $(G, P)$  satisfies the Markov condition (and thus is a Bayesian network) if and only if  $P$  is equal to the product of its conditional distributions of all nodes given their parents in  $G$ , whenever these conditional distributions exist.

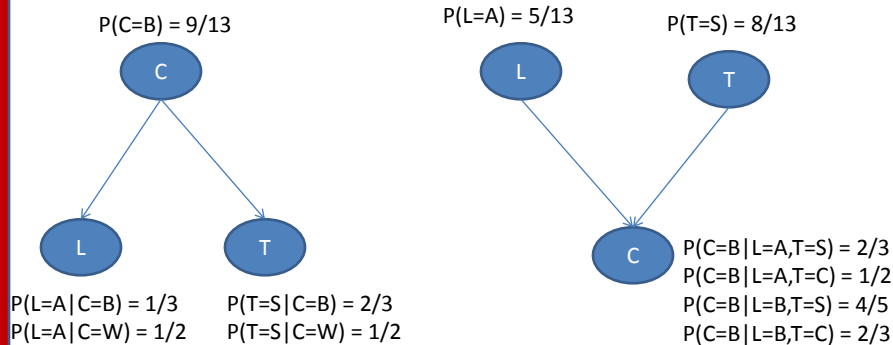
## Caveat

- It is important to realize that we can't take just any DAG and expect a joint distribution to equal the product of its conditional distributions in the DAG.

## Example Data

L	T	C
A	S	B
A	S	B
B	S	B
B	S	B
B	S	B
B	S	B
A	C	B
B	C	B
B	C	B
A	S	W
B	S	W
A	C	W
B	C	W

## Example



- Which one of the above DAG satisfies the Markov condition?

## Paradox

- Our goal is to represent a joint probability distribution succinctly using a DAG and conditional distributions for the DAG (a Bayesian network) rather than enumerating every value in the joint distribution.
- However, we don't know which DAG to use until we check whether the Markov condition is satisfied, and in general, we would need to have the joint distribution to check this.

## Paradox (Cont'd)

- A common way out of this predicament is to construct a causal DAG, which is a DAG in which there is an edge from  $X$  to  $Y$  if  $X$  causes  $Y$ .
- A second way of obtaining the DAG is to learn it from data.