To do this, we introduce the notion of \textit{definition-dependent} (longer than or equal to) node. A node is definition-dependent on another if its value is determined by the other node. Moreover, given the Markov property, it is possible to determine whether the outcomes of a node depend on the outcomes of another node.

These outcomes apply only to the presence of a single node, but also to the presence of sets of nodes that between them.

We have seen how Bayesian networks represent conditional independences. Let's look at the two.

**2.4.2 Conditional Independence**

\[ P(A \mid B, C) = P(A \mid C) \]

We refer to this as conditional independence between two events.

**Completeness Again**

In order to have a full understanding of the completeness of a Bayesian network, we need to understand the concept of causal models. A causal model is a set of structural equations that describe how variables in the network interact.

\[ P(A \mid B, C) = P(A \mid C) \]

We refer to this as conditional independence between two events.

**2.4.3 Common Effects**

If there is no evidence of information about can, then learning that can, the probability of an event will increase the chances of cancer, which in turn will increase the probability of the event.

\[ P(A \mid B, C) = P(A \mid C) \]

We refer to this as conditional independence between two events.

Consider a causal chain of three nodes, where $A$ is evidence, $B$ is a cause, and $C$ is an outcome.

**2.4.4 Causal Chains**

We refer to this as conditional independence between two events.
Example Statement: Suppose that we want to expand our original medical classification system to represent explicitly some other possible causes of chronic illness.

2.3 As an example, suppose the two nodes A and C are connected by a single edge, but there is no path between them. Then, there is a way to classify the patients into distinct groups based on the presence or absence of each of these conditions.

A BN representation of this medical decision problem is shown in Figure 1. The nodes A and C are connected by a single edge, and there is no path between them. This representation allows us to consider the relationships between the different conditions and their potential effects on the overall diagnosis.

Example Statement: Knowing that a new patient’s diagnosis is based on a medical decision-making algorithm, we can expand our original system to include additional categories for potential diagnoses.

2.5 Example: Consider the decision diagram shown in Figure 2. a) A path from X to Y can be found by following the edges in the diagram. b) A path from Y to Z can be found by following the edges in the reverse direction. c) A path from X to Z cannot be found by following the edges in any direction.

Definition 2.1: A path (and directed path) from node X to node Y is a sequence of nodes that form a path from X to Y.

Definition 2.2: A block (undirected path) from node X to node Y is a sequence of nodes that form a path from X to Y, where at least one of the nodes is not connected to any other node in the sequence.

Figure 2:

Graph A

- A
- X
- Y
- Z

Graph B

- A
- X
- Y
- Z

Graph C

- A
- X
- Y
- Z

Graph D

- A
- X
- Y
- Z

Graph E

- A
- X
- Y
- Z

Graph F

- A
- X
- Y
- Z

Graph G

- A
- X
- Y
- Z

Graph H

- A
- X
- Y
- Z

Graph I

- A
- X
- Y
- Z

Graph J

- A
- X
- Y
- Z

Graph K

- A
- X
- Y
- Z

Graph L

- A
- X
- Y
- Z

Graph M

- A
- X
- Y
- Z

Graph N

- A
- X
- Y
- Z

Graph O

- A
- X
- Y
- Z

Graph P

- A
- X
- Y
- Z

Graph Q

- A
- X
- Y
- Z

Graph R

- A
- X
- Y
- Z

Graph S

- A
- X
- Y
- Z

Graph T

- A
- X
- Y
- Z

Graph U

- A
- X
- Y
- Z

Graph V

- A
- X
- Y
- Z

Graph W

- A
- X
- Y
- Z

Graph X

- A
- X
- Y
- Z

Graph Y

- A
- X
- Y
- Z

Graph Z

- A
- X
- Y
- Z