

Introduction:

This project seeks to utilize a particular kind of network called a Bayesian Network to guess what might occur in a medical situation by looking at things like how the patient is doing, test results, and what treatments they might get. This report clarifies how we created and tested the Bayesian Network for this job.

Problem Statement:

In this project, we're making a sample of a medical situation using Bayesian Networks. The idea is to figure out the possibilities of further things happening based on the patient's condition, test results, treatment choices, and what occurs next.

Bayesian Network Structure Design:

Bayesian Network structure design is created around four essential elements: A (Patient Condition), B (Test Result), C (Treatment Decision), and D (Outcome). The connections between these nodes are as follows: [('A', 'B'), ('A', 'C'), ('B', 'C'), ('C', 'D')]

Implementation Details:

- The Bayesian Network is assembled employing the **pgmpy** library.
- Every node brings its own set of options, called Conditional Probability Distributions (CPDs).
- To figure out possibilities, we use the Variable Elimination method.
- We ask various questions to figure out the prospects of additional things occurring, like what might happen and how treatments could impact it.

Evaluation Results:

- Probabilities are estimated for patient condition (A), test result (B), and treatment decision (C).
- These possibilities indicate how each thing is extended out.
- Guesses are created for outcomes (D) and treatment decisions (C) based on observed proof.
- The effect of medicines on results is analyzed.

Insights Gained:

The Bayesian network benefits from medical judgments utilizing probabilities. Here's what we understood and learned:

- We understand and learn how possible various patient conditions, test results, and treatment decisions are.
- We can expect what might occur based on what we've seen.
- We checked and learned how keen the results are for different treatment options.

Conclusion:

The Bayesian Network forecasts medical outcomes based on patient condition, test results, and treatment choices. It demonstrates how sufficiently these networks can create precise predictions in medical conditions, proving their point in complicated procedures.

Output:

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Probability distribution of Patient Condition A:
+-----+
| A | phi(A) |
+-----+
| A(0) | 0.7000 |
+-----+
| A(1) | 0.2000 |
+-----+
| A(2) | 0.1000 |
+-----+
Probability distribution of Test Result B given that patient's condition is poor:
+-----+
| B | phi(B) |
+-----+
| B(0) | 0.3000 |
+-----+
| B(1) | 0.7000 |
+-----+
Probability distribution of Treatment Decision C given that patient's condition is fair and the test result is negative:
+-----+
| C | phi(C) |
+-----+
| C(0) | 0.3000 |
+-----+
| C(1) | 0.7000 |
+-----+
Probability distribution of Outcome D given that patient's condition is fair, the test result is positive, and the treatment decision is not treated:
+-----+
| D | phi(D) |
+-----+
| D(0) | 0.2000 |
+-----+
| D(1) | 0.8000 |
+-----+

Finding Elimination Order: : : 0it [00:00, ?it/s]
0it [00:00, ?it/s]
Most likely outcome D: 1
Finding Elimination Order: : : 0it [00:00, ?it/s]
0it [00:00, ?it/s]
Predicted Treatment Decision C: 0
Sensitivity of outcome D to changes in treatment decision C: [0.6 0.6]
Probability distribution of patient's outcome D under different combinations of conditions:
Combination (A=0, B=0, C=0): [0.8 0.2]
Combination (A=0, B=0, C=1): [0.2 0.8]
Combination (A=0, B=1, C=0): [0.8 0.2]
Combination (A=0, B=1, C=1): [0.2 0.8]
Combination (A=1, B=0, C=0): [0.8 0.2]
Combination (A=1, B=0, C=1): [0.2 0.8]
Combination (A=1, B=1, C=0): [0.8 0.2]
Combination (A=1, B=1, C=1): [0.2 0.8]
Combination (A=2, B=0, C=0): [0.8 0.2]
Combination (A=2, B=0, C=1): [0.2 0.8]
Combination (A=2, B=1, C=0): [0.8 0.2]
Combination (A=2, B=1, C=1): [0.2 0.8]
C          D=Positive      D=Negative
treated    0.2             0.8
not treated 0.8             0.2
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