KRR - Conditional Independence in Bayesian Networks

Tudor Berariu, Alexandru Sorici

November 2018

1 Conditional Independence and D-separability

This tutorial focuses on the concepts of *conditional independence* and *d-separabilty* in Bayesian Networks. The definitions below skip a lot of details and do not offer proofs as their role is only to bridge the aforementioned notions.

A Bayesian Network is a probabilistic graphical model that compactly represents a joint distribution over a set of random variables \mathcal{X} . More precisely, a Bayesian Network is a directed acyclic graph \mathcal{G} having a node for each random variable in \mathcal{X} . Each edge in \mathcal{G} corresponds to a direct causal influence from one variable to another. One of the strengths of this representation is that it captures conditional independence assumptions about the random variables in \mathcal{X} .

We are interested in evaluating conditional independence assertions of the form $(\mathbf{X} \perp \mathbf{Y} \mid \mathbf{Z})$ where $\mathbf{X}, \mathbf{Y}, \mathbf{Z}$ are all disjoint subsets of \mathcal{X} . The semantics of such an expression is Assuming that \mathbf{Z} is known would observing \mathbf{X} bring any information (change our belief) about the variables in \mathbf{Y} ?.

The conditional independencies in \mathcal{G} correspond to *d-separation* relations between variables: $(\mathbf{X} \perp \mathbf{Y} \mid \mathbf{Z}) \iff dsep_{\mathcal{G}}(\mathbf{X}; \mathbf{Y} \mid \mathbf{Z}).$

We state that \mathbf{X} and \mathbf{Y} are d-separated given \mathbf{Z} if there are no *active paths* between any node $X \in \mathbf{X}$ and $Y \in \mathbf{Y}$ given \mathbf{Z} . In other words, \mathbf{X} and \mathbf{Y} are d-separated given \mathbf{Z} if information does not flow between the two sets of random variables.

A path in \mathcal{G} : $X_1 - X_2 - X_3 - \ldots - X_N$ is active given **Z** if all its trails of two consecutive edges $X_{i-1} - X_i - X_{i+1}$ are active given **Z**.

Simple rules can be applied to analyse if a trail $X_{i-1} - X_i - X_{i+1}$ is active given **Z**:

- Causal trail: $X_{i-1} \to X_i \to X_{i+1}$ is active if $X_i \notin \mathbf{Z}$ (X_i is not observed);
- Evidential trail: $X_{i-1} \leftarrow X_i \leftarrow X_{i+1}$ is active if $X_i \notin \mathbf{Z}$ (X_i is not observed);
- Common cause: $X_{i-1} \leftarrow X_i \rightarrow X_{i+1}$ is active if $X_i \notin \mathbf{Z}$ (X_i is not observed);
- Common effect: $X_{i-1} \to X_i \leftarrow X_{i+1}$ is active if $X_i \in \mathbf{Z}$ or any of the descendants $D \in desc_{\mathcal{G}}(X_i) \in \mathbf{Z}$ (X_i or any of its descendants is observed);

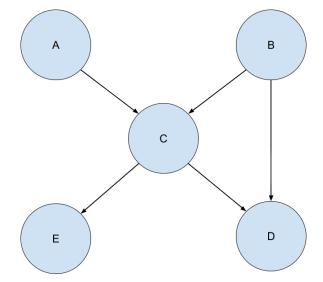
2 Tasks

Design an algorithm to check independence assumptions $(\mathbf{X} \perp \mathbf{Y} \mid \mathbf{Z})$ in a Bayesian Network. A simple idea would be to explore the graph \mathcal{G} starting from the nodes in \mathbf{X} following active trails given \mathbf{Z} . If at any point a node from \mathbf{Y} is reached, then the independence does not hold. Otherwise, if \mathbf{Z} blocks all the paths from \mathbf{X} to \mathbf{Y} , d-separating the two sets of nodes, then the conditional independence holds.

You are given test files containing the graph structure, various queries, and the correct answers. Such a file has the following structure (1 + N + 2M lines):

- two positive numbers on the first line: N the number of nodes in \mathcal{G} , and M the number of queries;
- N lines with the name of each variable followed by the names of its parents;
- *M* lines containing queries expressed as a sequence of names from **X**, the '';'' symbol, the names from **Y**, the ''|'' symbol and then the names of all observed variables from **Z**;
- M lines containing either ''true'' or ''false'' corresponding to the correct answers of the M independence queries.

3 Example



5 8
A
B
C A B
D C B
E C
A B; E |
A B; E | C
E; D |
E; D | B
E; D | C
A; B |
C A; B | D
false
true
false
false
false
false
false

