Building Bayesian Influence Ontologies
Literature Review

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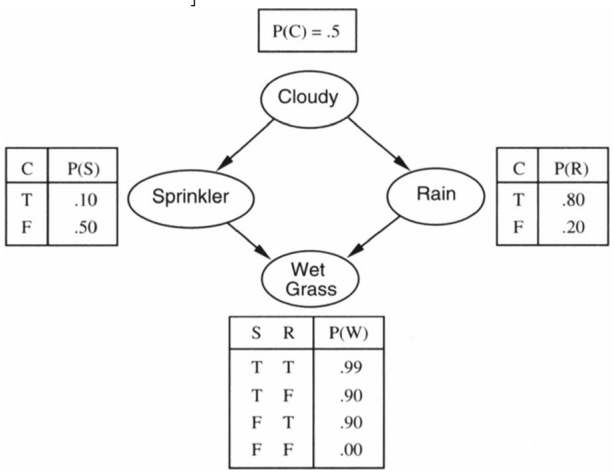
1 Introduction

2 Similarity Metrics

3 Bayesian Networks

When considering a joint probability distribution across n random variables, classical probability states that the number of parameters needed to represent the distribution grows exponentially in n [Koller and Friedman 2009]. Even in the simple case of binary variables, we would still need $2^n - 1$ parameters to describe the distribution. This is clearly unfeasible for practical applications, in which the number of random variables can grow very large.
Bayesian networks, originally developed by Pearl [1988], present a way of reducing the number of parameters needed to represent a joint distribution. A Bayesian network is a directed acyclic graph (DAG) whose nodes represent random variables and whose edges represent influence of one variable on another. This structure can also be thought of as a representation of the conditional independencies between the random variables [Koller and Friedman 2009]. Indeed, it is through the exploitation of these independency assumptions that a Bayesian network can more compactly represent a joint distribution.

Figure 1: A famous example of a Bayesian network, showing how a complete representation of any random variable X requires considering only those variables who are parents of X in the graphical representation [Norvig and Russell 1994].



An important notion in Bayesian networks is that of d-separation, first presented by Pearl [1986], which is used to find the set $\mathcal{I}(\mathcal{G})$ of conditional independencies in the graph $\mathcal{G}$. $\mathcal{I}(\mathcal{G})$ is used as the basis for an equivalence relation, I-equivalence, for which any two I-equivalent graphs represent the same independency assumptions [Verma and Pearl 1991]. An important developement by Pearl [1986] is that any I-equivalence class can be represented as a partially directed acyclic graph (PDAG) in which undirected edges represent edges that can be oriented any way and still result in a graph belonging to the same class.

4 Structure Learning

The manual construction of networks is generally unfeasible for a large number of variables [Koller and Friedman 2009]. Fortunately, strategies exist to learn model structures from data $\mathcal{D}$.

4.1 Constraint-Based Structure Learning

One approach to the construction of model structures is the constraint-based approach, in which dependencies between variables are first queried and then, based on these dependencies, a PDAG is constructed [Koller and Friedman 2009]. This strategy can be traced back to Verma and Pearl [1991].
However, this approach is generally not preferred, as failure in the individual independence queries can lead to the construction of a network which poorly matches the data [Koller and Friedman 2009].

4.2 Score-Based Structure Learning

A more popular approach to the problem is score-based structure learning, in which entire networks are constructed and then evaluated and modified based on some scoring metric [Koller and Friedman 2009].

5 Bayesian Similarity

References

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