

Artificial Intelligence - Probabilistic Reasoning (14) - 1

Bayesian Network: A directed graph in which each node is annotated with quantitative probability info.

- It is a representation of joint probability distribution.
- It is encoding of a collection of conditional independent statements.

- A generic entry in JPD is the probability of a conjunction of particular assignments to each variable, such as $P(X_1=x_1, \dots, X_n=x_n)$ abbreviated as $P(x_1, \dots, x_n)$. The value of this entry is given by formula -

$$P(x_1, \dots, x_n) = \prod_{i=1}^n Q(x_i | \text{parents}(X_i)). \text{ where}$$

$\text{parent}(X_i)$ denotes the value of $\text{Parents}(X_i)$.

- Bayesian Network can too answer any query, by summing all relevant joint entries.

- Locally structured system: A component in LSS interacts directly with only a bounded no. of components.

- In fully connected Bayesian NW,

- Topological Semantics of BN: Specifies the conditional independence relⁿ encoded by graph structures.

+ Specifies that each ~~node~~ ^{node} variable is conditionally independent of its non-descendants.

+ Markov blanket: A node is conditionally independent of all other nodes, given its parents, children & children's parents.

- The basic task of any probabilistic inference system is to compute the posterior probability distribution for a set of query variables, given some observed event - that is, some assignment of values to evidence variables.

- A query can be answered using

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$$P(X|e) = \alpha P(X, e) = \alpha \sum_y P(X, e, y)$$

+ A query can be computed using Bayesian NW by computing some of products of conditional probabilities from the network. (Inference by enumeration)

+ Enumeration algo can be improved substantially by eliminating repeated calculations. one approach variable elimination algo:

- Singly connected networks / Poly trees: Contains at the most one undirected path betw any 2 nodes in the network

+ Time & Space complexity is linear in size of the network.

- Multiply connected networks \nexists contains more than one undirected paths betw any 2 nodes.

- Clustering Algos

+ Variable elimination is less efficient in computing posterior probabilities. Total time $O(n^2)$

+ Clustering Algo: Time total $O(n)$

+ Joins individual nodes to form clusters to create ~~singly~~ polytree.

Approximate Inference in Bayesian Network

Method 1: Direct Sampling Methods

- Generates events from a Network that has no evidence associated with it.

~~The~~ The frequency of sampling a specific event converges, in the limit, to expected value according to the event's sampling probability

- An estimated probability becomes exact in large sample limit. Such an estimate is called ~~con~~ consistent.

Method 2: Rejection Sampling.

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- Rejects samples that are not consistent with the evidence
- Given $P(X|e)$, the algo. first generate samples from prior distribution & reject those that are not consistent with the given evidence
- Produces a consistent estimate of the true probability
- Rejects too many samples.

Method 3: Likelihood weighting

- Avoids inefficiency with rejection sampling by generating only events that are consistent with e
- Suffers a degradation in performance & no. of e increases. Because most samples will have very low weights & \therefore the weighted estimate will be dominated by tiny fraction of samples that accord more than an infinitesimal likelihood to evidence.

Method 4: Markov Chain Monte Carlo (MCMC) Algo.

- Makes random change to preceding event in previous event. ~~Ass~~ Network can be assumed to be in current state. specifying value for each variable.
- Next state is generated by randomly sampling one of the non-evidence variables: condition on current values of variables in the Markov blanket.

* Markov blanket of a variable consists of its parents, children & other parents of its children.

Extending Probability to First-order representation (4)

- First order probabilistic KB should specify probabilities for all possible first order models.
- For any FO sentence ϕ , the probability $P\phi$ is given in the usual way by summing over possible worlds where ϕ is true;

$$P\phi = \sum_{M: \phi \text{ is true in } M} u(M) \quad , \text{ where } u(M) \text{ is model prob.}$$

- Relational Probability Model can be used to represent FO Models.

- Ashish R. Gavarde