Knowledge representation, communication, and update in probability-based multiagent systems

(Extended Abstract)

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ABSTRACT

The goal of this thesis is to allow easier design of probability-based agents and multiagent systems, resulting in rational decision making. A multiagent framework is presented and compared with other proposed frameworks where advantages and disadvantages of each are outlined. A central problem of message passing in probabilistic systems is the familiar rumor problem, where cycles in message passing cause redundant influence of beliefs. We develop algorithms to identify and solve the rumor problem in the context of our multiagent system. Central to our message passing scheme is the notion of soft evidential update. Traditional propagation algorithms are not compatible with soft evidence. We propose a new propagation algorithm that is based on Lazy propagation and compare the theoretical and experimental performance with other proposed solutions.

Categories and Subject Descriptors

I.2.3 [**Artificial Intelligence**]: Deduction and Theorem Proving—*Uncertainty, "fuzzy," and probabilistic reasoning*; I.2.11 [**Artificial Intelligence**]: Distributed Artificial Intelligence—*Coherence and coordination, Intelligent agents, Multiagent systems*

General Terms

Algorithms, Design, Theory

Keywords

Communication protocols, Distributed problem solving, Knowledge representation, Reasoning (single and multi-agent)

1. RESEARCH GOALS

In this dissertation, we define a cooperative multiagent system where the agents use locally designed Bayesian networks or Influence diagrams to represent their knowledge. Agents communicate via message passing where the messages are beliefs in shared variables that are represented as probability distributions. Messages are treated as soft evidences in the receiver agents, where the belief in the receiving agent is replaced by the publishing agents belief. We call this the oracular assumption, where one agent is an expert or more knowledgeable of particular variables. As a result, the agents are organized in a publisher-subscriber hierarchy. A central problem of message passing in probabilistic systems is the so called rumor problem, where cycles in message passing cause redundant influence of beliefs. We develop algorithms to identify and solve the rumor problem in the context of our multiagent system. Our multiagent system is contrasted with another related agent model MSBNs [9].

Central to our multiagent system is the notion of soft evidential update. We develop methods to efficiently perform probabilistic update in Bayesian networks and Influence diagrams where the soft evidence is respected. We analyze the theoretical and experimental complexity of our methods and compare them with other methods that have been proposed.

Finally, we implement several multiagent systems for experimentation using our mulitagent system and MSBNs. We devise performance measures to compare the two systems. From this comparison, we provide guidance for the design of probabilistic multiagent systems.

2. PROBABILISTIC MULTIAGENTS

Probabilistic multiagents, utilize joint probability distributions to represent knowledge, and communicate beliefs. In this dissertation, we expand the Agent Encapsulated Bayesian Network (AEBN) framework originally proposed by Bloemeke [1, 6]. This dissertation aims to expand and correct technical details, as well as provide a theoretical basis for AEBNs. A comparison with other frameworks is presented to highlight the advantages and disadvantages of each, as well as argue for the role of AEBNs in designing probabilistic multiagent systems.

In an AEBN system the agents communicate through the transmission of probability distributions on shared variables. The topology of the communication in the multiagent system forms a DAG structure. The Bayesian network of each agent can be divided into three distinct sets of variables: I, those about which other agents have better knowledge; L, those that are used only within the agent; and O, those that this agent has the best knowledge of and that other agents may want. This effectively produces two classes of variables in the agent: its local variables, L, and its shared variables, I and O.

The mechanism for integrating the view of the other agents on a shared variable is to simply replace the agent's current belief in the variable with that of the communicating agent.

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For this reason, all communication in the AEBN system occurs through the passing of messages that essentially contain the "correct" views on some shared variables. When an agent receives one of these messages, it modifies its internal model so that its local distribution becomes consistent with the other agents' view.

3. THE RUMOR PROBLEM

It is well known that communication of probabilities among agents leads to potential double counting of information. This fundamental problem is due to mishandling of dependent or correlated variables and is known as the rumor problem [9]. In order to understand and identify redundant influences in a multiagent system, we define a communication graph, where the nodes represent agents and directed edges represent the flow of messages labelled with the shared variables that are being communicated.

It is sufficient to identify all redundant influences by examining all pairwise node disjoint paths in the communication graph. Once they have been identified, a new graph, known as the redundancy graph, is constructed. The redundancy graph has the same nodes and edges as the communication graph, but its edge labels are expanded if and only if there are redundant influences. We propose a method of compensating for redundant influences where agent communication has been expanded to pass joint probabilities along the appropriately labeled links in the redundancy graph, without any change in the local Bayesian networks of each agent. A data structure called the Redundancy Filter Tree is used to remove redundant influences from incoming messages before an agent performs belief propagation in its local Bayesian network.

We analyze the complexity of the proposed solution using simple parameters of the probabilistic multiagent system, as well provide formal proofs of its correctness.

4. SOFT EVIDENTIAL UPDATE

The issue of how to deal with uncertain evidence in Bayesian networks has recently been the subject of methological inquiry and algorithm development [8, 2, 7, 3]. Representing uncertain probabilistic evidence as virtual evidence is appropriate when we model the reliability of an information source, while the soft evidence representation is appropriate when we want to incorporate the distribution of a variable of interest into a probabilistic model. As observed by many authors, conditioning cannot be used to update beliefs in the presence of soft evidence.

The general soft evidential update method of [8] will be used in this dissertation; this general method admits several detailed algorithmic variants, which have different efficiency characteristics with respect to network topologies and evidence presentations. The input to the method consists of a Bayesian network and a set of soft and hard evidence. The method computes implicitly a joint probability that has two properties: (1) the evidence is respected; (2) the joint probability is as close as possible to the initial distribution represented in the input Bayesian network, where distance is measured by cross-entropy (I-divergence).

We analyze the performance of three algorithms for soft evidential update. The first algorithm is a new and improved version [4] of the big clique algorithm [8] that utilizes lazy propagation [5]. The second and third algorithms [7] are wrapper methods that convert soft evidence to virtual evidence, in which the evidence for a variable consists of a likelihood ratio. Virtual evidential update is supported in existing Bayesian inference engines, such as Hugin. To evaluate the three algorithms, we implemented BRUSE (Bayesian Reasoning Using Soft Evidence), a new Bayesian inference engine, and instrumented it. The resulting statistics are presented and discussed.

A soft evidential algorithm is presented to perform soft evidential update in decision networks.

5. EXPERIMENTAL ANALYSIS

The methods and algorithms defined in this dissertation are applied to a fictitious multiagent problem to investigate design challenges, performance and functional correctness of AEBNs. To compare and contrast, the same problem is implemented using Xiang's MSBNs [9]. Simple performance metrics are devised for comparison of beliefs and performance of the system.

Additional fictitious multiagent problems are devised to test the rational decision making capabilities of AEBNs. An AEBN system is constructed where an agent utilizes a hypothesis-driven influence diagram to make a decision based on evidence reported from other agents, and a more complex problem where an agent must make multiple sequential decisions.

6. REFERENCES

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