I J C T A, 9(15), 2016, pp. 7065-7072

Probabilistic Relational Model based approach for Decision Support Systems

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ABSTRACT

Decision making is a process of selecting the best and appropriate action among various alternative possibilities. Increase in popularity of Decision support systems in various domains is due to the factor that making intelligent decision in applications with curtailed information is critical. Techniques to build intelligent decision support system arise due to the complexity of making decisions in dynamically changing environment. This work presents a decision making support system using the approach of Probabilistic Relational Model (PRM) a sub discipline of Statistical Relational Learning which combines the probabilistic theory and statistics to address uncertainty in data and Relational learning to deal with complex relational structures. The system is designed using a Partially Observable Markov Decision Process (POMDP) model that is powerful yet flexible framework to model the assistive tasks. The proposed PRM framework is utilized to generate a general decision model for cognitive assistive technologies to provide assistance in health care application.

Keywords: *Decision Support Systems, Knowledge Engineering, Probabilistic relational model, styling, POMDPs.*

1. INTRODUCTION

Decision Support System are interactive, computer based system which includes a body of knowledge that specifies how to perform various tasks and specify what conclusions are valid in different circumstances. Machine learning which involves the design and building of computer systems is a subdivision of the larger discipline of Artificial Intelligence [15], that learns based on the experience. Machine learning methods have the prospective to manage the complexity and effectively support building of the DSSs under circumstances of uncertainty. Knowledge representation and knowledge engineering are central to AI research. Numerous problems which machines are expected to solve will require widespread understanding about the world. SRL [2] is a integration of statistical learning and relational learning which addresses uncertainty in data and deals with complex relational structures to model a joint distribution over relational data. The specific model used here is the Probabilistic Relational Model, or PRM [3]. A large section of real-world data is stored in relational database structures. On the contrary, SLR methods work with flat data illustrations. Thus, by applying these methods, much of the relational structure present in database is lost since data is converted into a flat form. This paper builds on the recent work on Probabilistic Relational Models (PRMs), and describes how to learn them from databases. Probabilistic Relational Models are established on representative basis of relational logic. PRMs combine logical representation with probabilities based on directed graphical models. The theory of objects to deal with relational data in PRM is extended form Bayesian networks.

Relationships between objects are modeled as primary/foreign key constraints or by extra tables which represent relationships/links. The key property of PRMs is that object’s property can be characterized

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either as attributes of classes and tables. POMDP models deal with uncertainty and are a powerful, nonetheless flexible framework for assistance modeling. POMDP models are temporal probabilistic model that denotes a decision making process based on data from the world and environmental study. A precise solution to a POMDP gives in the most advantageous action for each potential belief over the environment which increases the expected reward. Decision makers confront with gradually mounting difficult environments. Decision making under these perilous and uncertain conditions are supported by refined aids by using the arrangement of the Internet facilitated speed and access, and the maturation of artificial intelligence approaches.

This paper concerns the use of planning and decision technology where (i) non-experts are required to possess knowledge (ii) multiple planning and scheduling task are done with the information form knowledge base (iii) it may encounter unanticipated actions and decisions should be made to give assistance. The technical challenge of building, sensing and representing decision making system is to make decision that allows to be conveyed only at the suitable time is hard but achievable and accomplishable by end users using the Knowledge engineering approaches that specifies the sophisticated decision-theoretic control systems to sense what the users are performing and respond according to the needs and prerequisites. PRMs endorse the property of an object to depend probabilistically on other properties of that object and on of associated objects. A decision system should be designed so as to decide what the next action or assistance is when a person is performing more than one action at a time. An automatic production of decision systems would considerably ease the manual efforts in creating assistance systems, which are personalized to set of situations, tasks and environments. In general, the solution to unanswered research query in the design of support systems is the utilization of a priori knowledge. Study of people's behaviours from the data present and available is a major setback in the construction of intelligent technologies since actions need to be acknowledged, rational conclusion have to be drawn by including domain definite expert knowledge which eventually facilitate the environment to execute suitable actions. Significant changes are to made in each new task to produce a effective and operational aiding system, where massive expert knowledge is currently required for generalization and broader applicability to different tasks. This paper proposes a methodology to develop a decision-making aid tool to assess the dependability and performances of a system where the model is based on Probabilistic Relational Model formalism, which is adapted to deal with large and complex systems.

2. RELATED WORK

Cognitive Assistive technologies have been the focus of a great deal in research among the artificial intelligence community. The provision of general assistance and support in the completion of ADLs has undergone many studies. Ledisi giok kabari et al [8] proposed a Decision tree-neuro based model by applying hybrid integrations of Decision Tree and Artificial Neural Networks with Multilayer Feed-forward technique which predicts risk connected with each action. But it was not able to possibly plan for all contingencies that arise from a decision due to the inability to trace relationships between events, and such oversights led to bad decisions. Jesse Hoey et al [11] explains that Markov decision processes (MDPs) with large state spaces have become the semantic model to allow dynamic programming of choice for decision theoretic planning (DTP) in the AI development community with decision tree illustration of reward function. The drawback was the difficulty in dealing with multi-valued variables. J.Boger et al [6] designed a system which combines a Bayesian sequential estimation framework with a decision-theoretic framework for computing policies of action using a point-based approximate solution technique . The decision making system is a POMDP which is used to robustly optimize the course of action. Varaibles which are not directly observable pose a problem. J.Jessey Hoey et al. [4] presented a general decision theoretic model of interactions between users and cognitive assistive technologies. The model is a Partially Observable Markov Decision Process (POMDP) whose goal is to conclude a given activity to be done by the user. The model deals with the outcomes of ambiguous actions and is able to be suitable for users and tasks after learning and adapting over time. But the system did not incorporate user attitude modeling, planning or prompting and no indication or learning of the reward function. Jesse Hoey et al[10] Use algebraic decision diagrams *(ADDs)* to represent value functions and policies. Difficulty was in allowing ADDs to deal with multi-valued variables. Alex Mihailidis et al [9] studied and examined the efficacy of a computerized device intended to assist people with dementia through ADL, while reducing manual work. The COACH device uses artificial intelligence to autonomously provide guidance. The COACH system presented tracks the activity with the use of a POMDP to model the hand washing guidance problem and the refinement of prompts given to the users. The method of tracking used in this system is quite robust and is able to dependably track the location. Craig Boutilier et al [5] proposed a Dynamic programming approach for the solution of first-order Markov decisions processes. Algorithms are all designed to work with propositional representations of MDPs. L. Chen et al. [13] Logical framework for cognitive behavioral modeling, reasoning and assistance which is based on a highly developed logical theory of actions. The limitations was the level of granularity at which cognitive modeling is conducted, and the approach to scale to large complex system. Pascal Poupart et al [16] modeled the uuncertainty in the action effects and the state of the world probabilistically. Design of suitable control policies for automated systems. Intractability of existing solution algorithms. J.Hoey et al [7] proposed a assistive prompting system which successfully uses a Partially observable Markov decision process (POMDP) to assist people with dementia. In this work they described a method for automatically generating activity recognition automatically and context-sensitive prompting systems for complex tasks.

3. PROPOSED SYSTEM

Formalization and automation of the POMDP specification translation process is done using a Probabilistic Relational Model (PRM) encoded in a relational database. Fig 1 shows the system architecture which consists of the components Knowledge Base, Interaction Unit (IU) Analysis[12], POMDP Specification, Probabilistic Relational Model, Conditional Probability Tables(CPDs). The database encodes the relational framework of the PRM, and consists of the goals, action prerequisites, environment states, cognitive model, user and system behaviours and the result of the SNAP analysis. Probabilistic Relational Model (PRM) defined as a relational database that encodes a domain independent relational dynamic model and work to intervene the translation between the IU analysis and the POMDP specification. The database, when filled, unconditionally describe a ground instance of the relational skeleton, which is obtained using an computerized procedure, thus producing a POMDP model for the required assistance task. Enhanced planning and decision making techniques necessitates massive specialist knowledge for generalization and expansive applicability to diverse tasks. An automatic generation of such support systems would significantly diminish the manual guidance efforts necessary for building assistance systems. This work derives a methodology for specifying POMDPs for intelligent user assistance which is motivated by relational modeling in frame-based SRL methods. A key problem in the construction of intelligent technologies is the regular analysis of people’s behaviors from sensory information. Actions need to be acknowledged and, by incorporating domain specialist knowledge reasonable conclusions are drawn which in due course enables to take appropriate decision. Key challenges of developing such useful prompts are modeling a system that allows decisions to be delivered only at the appropriate time. This is tackled through the use of sophisticated development and decision making approaches. Decision Making System is designed through Probabilistic Relational Model (PRM) that handles uncertainties and provides Context based reasoning in the system.

3.1. Knowledge Base

The knowledge base consists of information regarding the user behavior and ADL that include tasks, duties, and actions. It specifies the task to be carried out and the actions to be performed. The relational database presents a natural association between the two elements of the decision support system, and the use of the database to additionally represent a novel approach to knowledge engineering (KE) for planning.

3.2. Interaction Unit Analysis

The emphasis in task analysis is on relating the actions taken by a user and the intentions goals and sub-goals that give rise to those actions. Interaction Unit Analysis breaks down the ADL into abilities and behaviours. IU Analysis uncovers the states and goals of the task which are to be performed in the sequential manner. The client abilities are broken down into:

- Recall
- Recognize
- Afford

Interaction Unit (IU) analysis, a expressively inspired technique for transcoding communications pertinent for fulfilling a definite task, is used to get hold of a formalized and machine interpretable task description.not mix complete spellings and abbreviations of units:

Recognition (Rn) requires the user to see or hear and understand the meaning with respect to the particular task.

Recall (Rl) requires the user to remember without being directly being able to see the required information.

Affordance (Af) implies recognition of the meaning of some part of the environment in terms of an action it makes possible.

The IU analysis ciphers the consequence of the action on the goal stack and the environment perfectly, in the course of the new goal assembly and important environment in the subsequent IU.

3.3. POMDP Specification

A POMDP for personal assistance breaks the state space down into three key factors states describing elements of the functional task in real world, states capturing the client's cognitive capacities, states capturing an what the client has actually done since the last update.

The factored POMDP for interactions with assistive technology consists the following components:

- T is the set of task variables,
- B represents behaviours of the client, and
- Y client's abilities.
- B and Y constitute the model of the client.
- A is the action of the system,
- R the reward, and

K and V are observations/sensors for task variables and client's behaviors correspondingly.

3.4. Probabilistic Relational Model

Probabilistic Relational Model (PRM) formalism permits to model real-world circumstances. Probabilistic Relational Models (PRMs) describe a outline for a probability distribution over characteristics of objects that specifies a solid probability distribution when grounded with specific data. The primary advantage of the PRM is that that association between classes can be acknowledged and classes can be distinguished. The conditional probability tables (CPTs) can be shared between numerous objects. The relational schemata of the PRM is symbolized by relational database where objects define the tables and derived tables which are resolute by queries, and attributes are defined as columns in tables. Associations between objects are

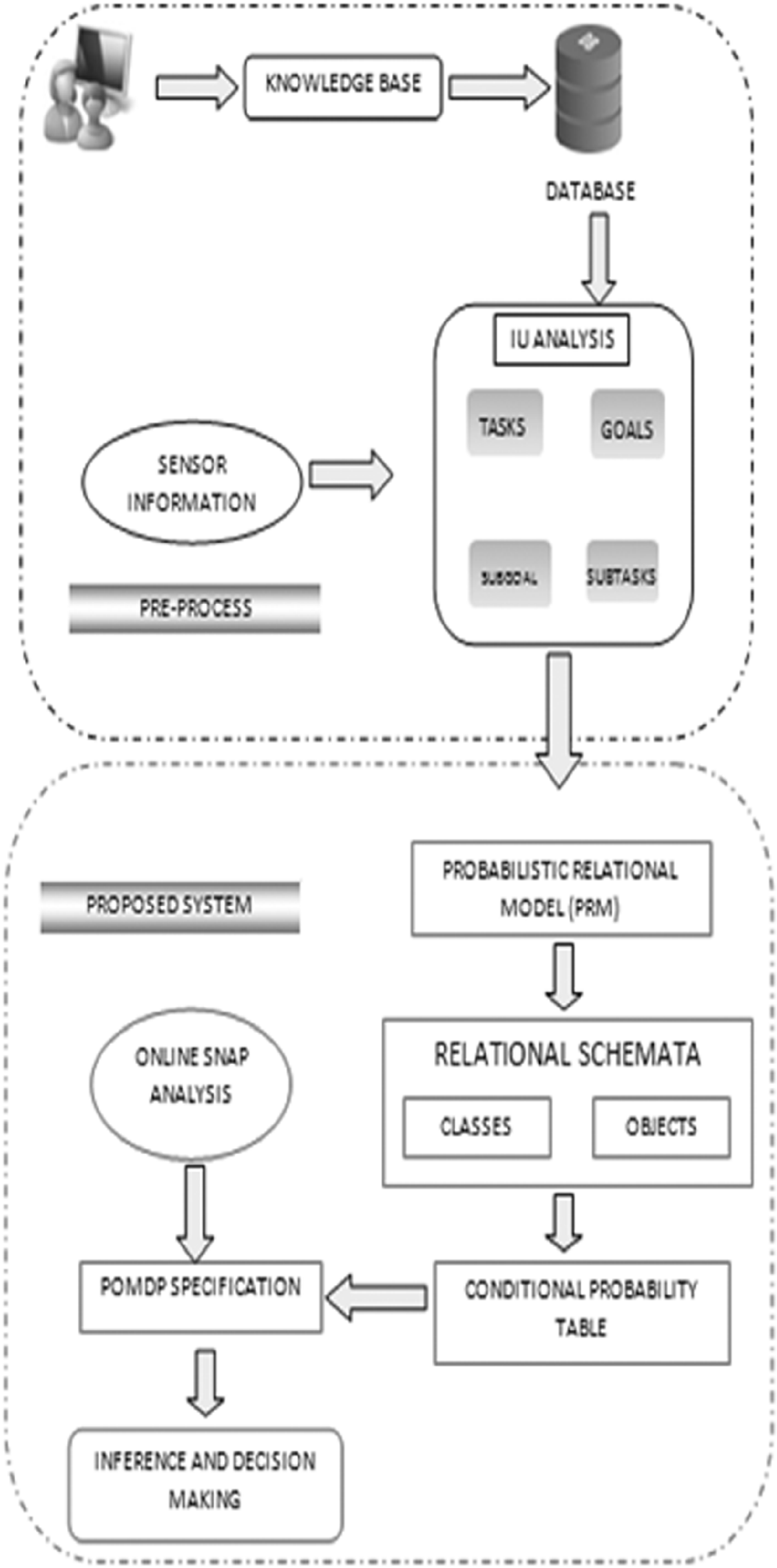

Figure 1: System Architecture for Decision Support Systems.

represented as constraints specified by primary or foreign key or by additional tables which represent relationships, association or links. The difference of the PRM when matching up to with other standard methods is their competence to deal with large complex domains and issues such as prediction, optimization, scrutiny of response, user experience, variation detection. The PRM is given out as a representation that can be instantiated for a exacting task using a straightforward and intuitive specification method.

The key property of PRMs that is exploited in this model is that properties of objects can be modeled r as attributes of classes/tables or as individual objects and connected with the main object using classes or tables which model relationships links. The probabilistic dependencies in the PRM are brought down to parameters that need to be specified to produce a working assistance system.

Bayesian network is learnt by Probabilistic Relational Model from a relational database in which all the information is stored. Dependency structure in the user information and knowledge is derived from the learning method of the PRM. In addition to the dependence structures, incorporates partial user knowledge, which can range from zero knowledge (similar to BN) to full knowledge (deterministic definition of output random variables).

Fig. 2 specifies the probabilistic model and its components. The relational schemata represent classes of objects, attributes of classes, and relations between classes through reference slots. Conditional probability distributions are required for every random variable. The relational frame provides specific objects which allow obtaining a probability distribution over attributes which are not observed directly by the skeleton framework. Conclusions about other associated entities are derived from relations among entities by using information present in the entities.

Unification allows sharing information among entities. Thus, it finds the general regularities for group instead of learning regularities for each single entity. The learned knowledge is often declarative and compact, which makes it easier to understand and to validate. This is important because background knowledge improve the quality of learning as it focuses the learning on the related outline.

The relational representation is the foremost constituent which is a specification of object types after normalization, their features, and associations connecting objects of detailed types. Further two components present in the system are for each attribute of the set of parents probabilistically depends on the equivalent conditional probability distributions tables CPD. In depth understanding of the system can be achieved by precise domain representation and constructive relationships are discovered. The models can be discovered

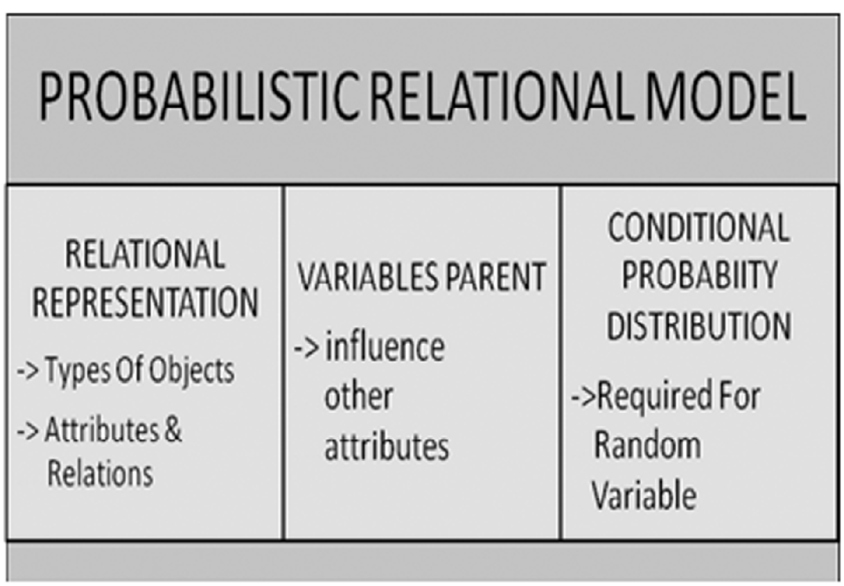

Figure 2: PRM Schemata

straightforwardly from an on hand database or knowledge base using well-substantiated statistical techniques in accumulation to providing a sound and consistent foundation for dealing with uncertainty encountered in real-world environment. Complex domains are modeled using PRM in terms of entity, their properties, and the associations between them. The uncertainty over the properties of an entity is characterized and the probabilistic reliance is capture over the properties of that entity and of related entities. Uncertainty over the relational structure can also be represented using PRM.

UnBBayes[17] is an open-source Java utility evolved by means of the Artificial Intelligence Group that affords a framework for building probabilistic graphical models and performing possible reasoning. It functions as a Graphical User Interface (GUI), an Utility programming interface, over and above plug-in support for unanticipated extensions. A Bayesian community(BN) is a graphical version based on Bayesian probability. It consists of a directed acyclic graph and a set of nearby probability distributions. Each node inside the graph represents a random variable, and the edges constitute direct qualitative dependencies of the random variables. The local probability distribution is a function (commonly represented as a Conditional probability table- CPT) specifying the quantitative information approximately the potency of the reliance. Every random variable has a set of possible values and precisely one of the feasible values could be the actual value at a given moment. The graph and the local distributions together are a compact illustration of a joint possibility distribution over the random variables. Reasoning structures based on Bayesian models depend on Bayes rule, which provides a method for updating the chance of a proposition while facts is received approximately a associated proposition.

The proposed methodology has originality on formalizing, by means of PRM, the models from prior knowledge on the crucial system functioning, and informational point of view to estimate the whole system.

3.5. Conditional Probability Tables

Conditional probability tables (CPTs) are parameterized, for a given type of attribute is the same in all possible objects and is reused for multiple objects. Aggregating functions are used on a flexible number of entities. PRM distinguishes more than one class, implying that relationships between classes can be identified and then conditional probability tables CPTs can be used among several objects. Particularly, aggregating policies support CPTs which depend on a changeable number of objects. The local probability distribution is a function specifying the quantitative information about the strong point of the reliance and the compact illustration of a joint probability distribution over the random variables. Each random variable A set of possible values is related to a individual random variable, and exactly one of the possible values will be the actual value at a given moment. The joint probability distribution over all variables can be factorized into product of the CPD of all the variables via the Chain Rule for Bayesian Networks as given in Equation 1

$$P\left(X_1,\dots\dots,\ X_n\right)=\prod_{i-1}^{n} P\left(x_i \middle| Pa\left(X_i\right)\right) \tag{1}$$

Five different CPTs for POMDP which shows the dependency structure.

Client abilities - *C*ompletion of specific steps of the task is reliable on the abilities that the client posses which depends on the actions that the system acquire.

Client behavior - *P*rior behavior, in progress ability and the preceding task state are factors upon which the client’s behavior depends .

Task state - The condition of the environment depends on its previous state and on the current behavior of the client.

Sensor information - Observations (sensors) are divided into states of sensors related to the task environment, states of sensors relevant to client behavior. *T*he sensors depend on one variable only.

Reward - Set of states and a reward value on each row is present as a reward function. Relative to each ability action costs are specified.

4. CONCLUSION

The proposed work is of a decision support system based on Probabilistic Relational model to provide assistance to people with cognitive disabilities. This system is about making intelligent and optimal decisions from incomplete information in unreliable environments which is critical in many applications. A firm foundation for working on preparation under uncertainty in action and observation is provided by POMDP. This system integrates the expert domain knowledge and the inference from the PRM to take the decisions which is motivated by relational modeling in SRL methods. In future the work can be extended as PRM online learning platform which is easily accessible to all.

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