2005

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## ABSTRACT

We describe a Bayesian Reasoning Framework (BRF) that supports business rule operations for on-line information systems. BRF comprises a three-layer environment with business information systems at the top, a middle-ware Bayesian reasoning server, and a Bayesian reasoning engine at the bottom. The top and middle-ware layers communicate via *SOAP/XML* protocol, while the middle-ware and bottom layers communicate via a Tag-value protocol that fetches business rules from a central repository. BRF is built as a Bayesian Reasoning Agent and tested in a helpdesk system for assigning advisors to users for trouble-shooting in the operation of business information systems. BRF is modeled following a use-case methodology as well as an inference modeling that uses an assignation template from Common-KADS. The concept, design and implementation of BRF for real-world, on-line business information systems are the main contribution of this research project.



### Keywords

Bayesian Reasoning, Bayesian Learning, Bayesian Inference, On-line Information Systems, Data mining, Common-KADS.


## INTRODUCTION

Information systems have changed their approach; from being transactional modular systems, they became integral systems that cover the operation of whole organizations. As a result of this evolution, a great volume of related transactions is produced, meaning that when produced by an integral information system, they include a strong relation among the business areas that produce them. To improve the use of the transactions generated by the organizations, the concept of Data Warehouse has evolved, along with the Artificial Intelligence (AI) techniques to use this information for analytic and decision making purposes. These techniques are known as Data Mining (DM) techniques (Berry and Linoff, 1997).

DM techniques are mainly applied as a consulting approach. A professional is hired by an organization for a specific application of DM in order to analyze the information and discover hidden patterns contained herein. He/She produces a model and utilizes it thereafter in the form of a computational program that implements a procedure that represents some convenient behavior found in the data to support and enhance the business decision process (Witten and Eibe, 2000). This approach is useful and produces a lot of benefits for organizations. Incorporating on-line DM techniques we are able to generate similar benefits as the ones with the consulting approach. That could be an important competitive advantage.

The companies that produce integral information systems must increase their competitive advantages. It is no longer just solving the business operation problem that may include whole corporative organizations, but providing elements for the analysis and decision making that turn the client's organization more productive. In the last years, the use of AI techniques in real applications has grown because of the considerable increment of computing power, allowing the construction of information systems that can make decisions similar to or better than those taken by a human specialist. One of such AI tools is Machine Learning (ML) (Mitchell, 1997). ML allows an autonomous agent representing a human expert, to have the capacity of learning and adapting to the environment, making decisions in front of incoming and known situations. They can work in an autonomous way without human intervention.

As a step forward, we propose and implement BRF as a working environment in which an on-line information system learns Bayesian relations (Heckerman, 1995) that exist in the data, and uses that knowledge to support business decision processes using Bayesian Inference (Huang and Darwiche, 1994).

BRF seeks to enforce a data mining specialist to remain focused developing algorithms that implement diverse techniques allowing its use by on-line information systems, avoiding in this way the need for the presence of the DM specialist. The information system will remain in continuous operation. It will invoke the required DM techniques in an autonomous way whenever necessary, advising the proper business processes for better business operation.

This paper is organized as follows: first, we present the BRF and describe its architecture and the implemented reasoning algorithms. In the next section, we explain the design and implementation of a case study including results analysis and performance comparison with other approaches executing the same tasks. Finally, we state the conclusion of the paper and future work.

## BAYESIAN REASONING FRAMEWORK

BRF uses a multi-layer architecture and includes a Bayesian Reasoning agent for which we implemented two AI techniques, one for Bayesian Learning and the other for Bayesian Inference (Huang and Darwiche, 1994). They were put available for use by several business information systems working on-line.

The resulting representation generated by a Bayesian learning technique is named a probabilistic model, and it is used by a Bayesian's inference procedure to make inferences within the operation of an on-line business information system. In this context, the process is named Bayesian Reasoning and is executed by an autonomous agent. By incorporating the agent into BRF, the information system will make an autonomous Bayesian reasoning. The application of the technique will be initiated by the information system, deciding when and over which data the model should be built, and interacting with the Bayesian inference algorithm applying the model to several cases coming in the on-line operation of the information system. The application of the model is performed without human intervention.

The main contributions of this research are as follows:

1. The framework design and the implementation of BRF including an autonomous agent that incorporates Bayesian learning and inference for enhancing the performance of on-line business information systems,
2. A real world application, showing the advantages and better solutions for the helpdesk on-line information system based on probability maximization for best advisors assignation.

## SYSTEM ARCHITECTURE

We took a central application server from an information systems development company [1] as a starting point. TCA has more that 20 years in this business and specializes in on-line business information systems. International operations in industrial sectors like hotel chains, hospitals and retailers are common customers. The TCA application server has been working for years in industrial implementations.

BRF comprises a three-layer environment with business information systems at the top, a middle-ware Bayesian reasoning techniques server (BRserver), and a Bayesian reasoning engine at the bottom.

The top and middle-ware layers communicate via *SOAP/XML* [2] protocol, while the middle-ware and bottom layers communicate via a Tag-value protocol that fetches business rules from a central repository providing Bayesian reasoning capabilities to the information systems. Figure 1 shows the BRF architecture.

### Top Layer: The Information Systems

This is the layer where the on-line information system is implemented, and it is regarded as a client for the BRF. Several communication tasks were implemented in the middle-ware using SOAP/XML.

The information system applications that communicate with BRF can be located elsewhere and in any platform. They can be implemented as independent applications, even as applications that demand a browser for its operation. The use of SOAP/XML protocol is mandatory for communicating with the middle-ware.

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[1] Thanks to Tecnología Computacional Aplicada (TCA), http://www.grupotca.com.

[2] W3C, Simple Object Access Protocol (SOAP), http://www.w3.org/TR/soap/

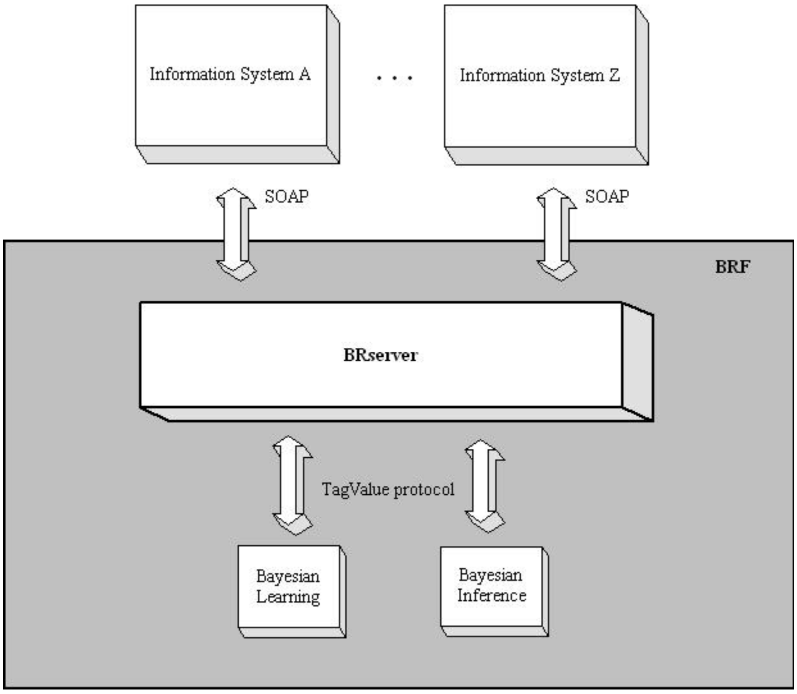


**Figure 1. BRF architecture.**

### Middle Layer: Bayesian Reasoning server (BRserver)

The BRserver is the middle-ware of the system and the layer that works as a link between the information system and the Bayesian reasoning engine. The main functions of the BRserver are:

- Control agent sessions from the client layer (information system).
- Control the execution of the Bayesian reasoning engine.
- Keep alive agent sessions, until the agent disconnects.
- Transform an unstable HTTP session into a permanent connection.

This is the way we maintain available the communication channels needed for the agents in the information system to access and use the required BR algorithms within the engine. The main function of BRserver is to act as a Bayesian reasoning engine facilitator for all the agents that may be logged on into several client sessions.

### Bottom Layer: Bayesian Reasoning engine

The Bayesian reasoning engine is implemented by learning and inference algorithms. Both algorithms were programmed in the 'C' language [3]. When the Bayesian reasoning engine executes the functions required from the Top Layer through the middle-ware, it returns the results encoding the information as a tag-value format.

## A CASE STUDY

As a case study we replaced the manual helpdesk service folio assignation by an agent that executes the CommonKADS (Schreiber et al., 2000) assignation method using Bayesian reasoning. The main goal of the helpdesk system is to provide technical support service through the internet to users of an integral information system for several hotel chains which are leaders in the Latin American market. Each hotel has between 10 - 40 users whose technical support requirements are attended by the helpdesk system. The helpdesk system works in the following way:

[3] Software available at http://www.grupotca.com/arobles/brf.

- When a user requires technical support, he logs into the helpdesk system and registers its needs in text form. The helpdesk immediately responds giving the user a service folio. This service folio will serve as a unique identification during the whole advisor service process.
- Using manual assignation, once the helpdesk service supervisor has received the new service folios, based on his experience, he assigns each folio to an advisor. The assignation goal is to provide the customer with the best possible service.
- The assigned advisor will provide support until the user's needs are completely satisfied.
- Once the user has the solution by the advisor, he proceeds to close the folio filling an evaluation form for the received service.
- As a service feedback, each month the helpdesk supervisor sends the hotel chain executives a service evaluation report including a summary about the service activities performed and the evaluation given by the users to each folio.

The implemented agent using the BRF replaces the manual assignation performed by the human supervisor. The agent assignation procedure is as follows:

- It sends to BRF the data corresponding to evaluations made by humans in a period of 3 years. BRF constructs a model with this data.
- Each time a service folio is entered by a user, the agent asks the BRF the advisor to which the folio should be assigned.
- Once the service folio is completed and evaluated, the agent sends to BRF the evaluation information for updating the probabilistic model. Since the probabilistic model is updated on line, it could be updated several times a day assuring the best possible advisor assignation.

### Methodology

The autonomous agent implementation was performed using the following methodology:

- We made the analysis and design for the agent specification as explained in section “System analysis and design”.
- The Bayesian learning and inference algorithms were programmed in the ‘C’ language.
- We implemented the advisor assignation method using the Bayesian reasoning engine which is made available by the BRF. To improve service quality, the agent assigns advisors using Bayesian inference, maximizing the probability of having the best evaluation and service time. For this reason, we can say that given the service history, using Bayesian reasoning through BRF the agent gets the advisor assignation that guarantees the best evaluation from the service folio owner.
- The interaction between the agent and the Bayesian techniques is only performed in the BRF context.

### System analysis and design

The system analysis was made following the CommonKADS (Schreiber et al., 2000) methodology. For the specification of the required agents, we utilized the multi-agent system MAS-CommonKADS approach. (Iglesias et al, 1996).

In order to delimit the scope of the system's functionality and to establish clearly the implementation role for the assignation method with Bayesian reasoning, we specify the problem domain as follows:

- The conceptual interaction diagram for the real world application using a use case diagram for the domain is shown in figure 2. The shaded area represents the assignation inference method. Bayesian reasoning is exploited here.
- The domain knowledge is presented as a classes diagram and is displayed in figure 3. This diagram represents the ontology that defines the terms used across the application.
- The assignation task and method, including its model and control diagram are depicted in figure 4.
- The required business rules for this application are illustrated in figure 5.

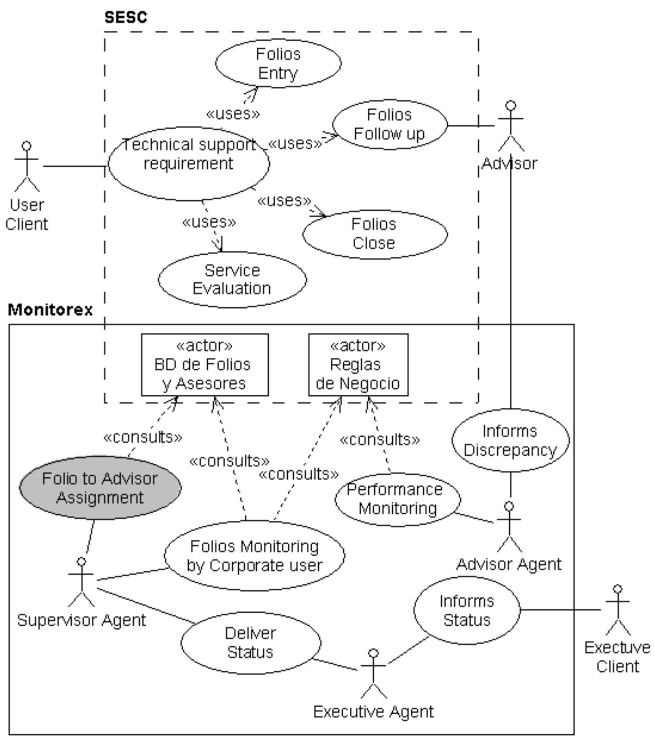


**Figure 2. Use Case Diagram**. The dashed lines delimits the functionality of the help desk system. The shaded area represents the Advisor Assignation implemented using BRF.

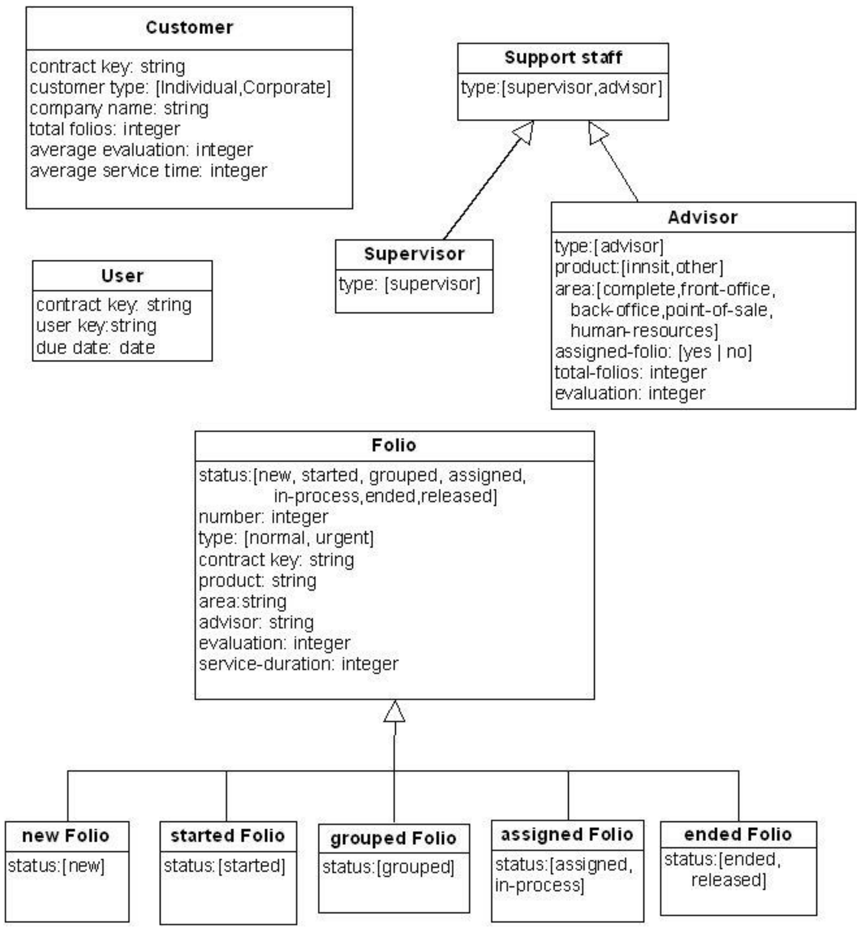


**Figure 3. Domain Knowledge (ontology).**

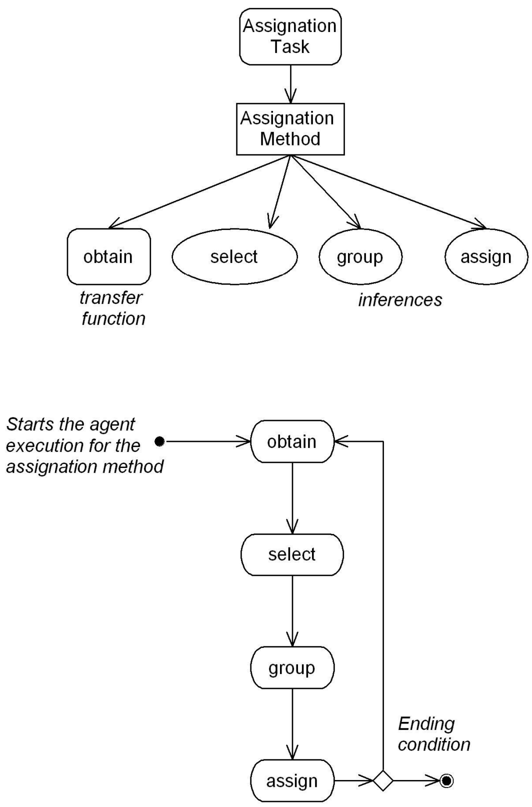


**Figure 4. Assignation Task.** Upper figure shows the task decomposition. Bottom figure shows the control diagram for the assignation method.

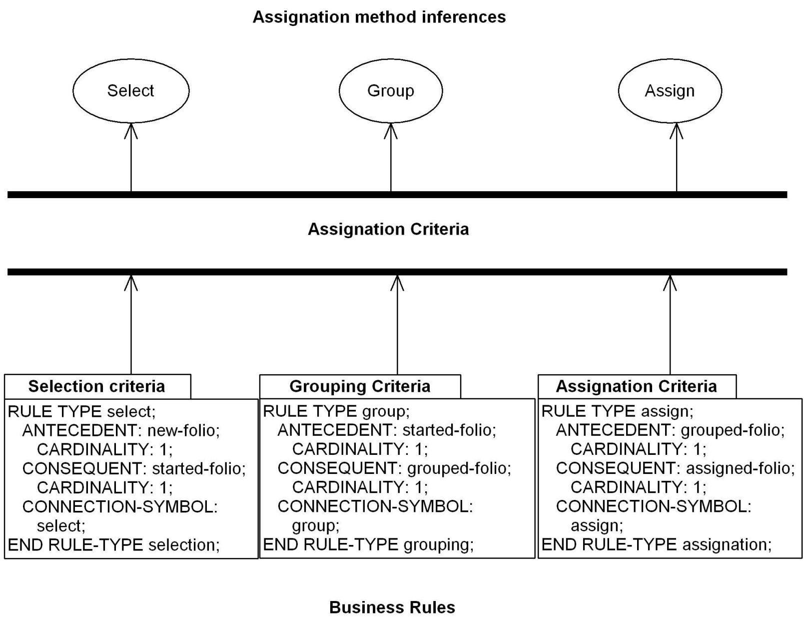


**Figure 5. Business Rules**. Assignation method inferences showing antecedents and consequents for each folio status specified by the ontology.

**Scope of the reasoning agent**

The autonomous agent uses the Bayesian learning algorithm for learning the advisors assignation pattern. The algorithm learns which advisor to assign to each folio depending on the characteristics of the required service.

The activity diagram for the assignation method shown in figure 6 describes the required method in which the agent controls the inferences. As shown in figure 6, we can integrate the Bayesian reasoning algorithms into the information system because of BRF. This working environment allows the information system to be built based in Bayesian reasoning techniques. The information system programmer does not take care of the implementation details of the Bayesian algorithms.

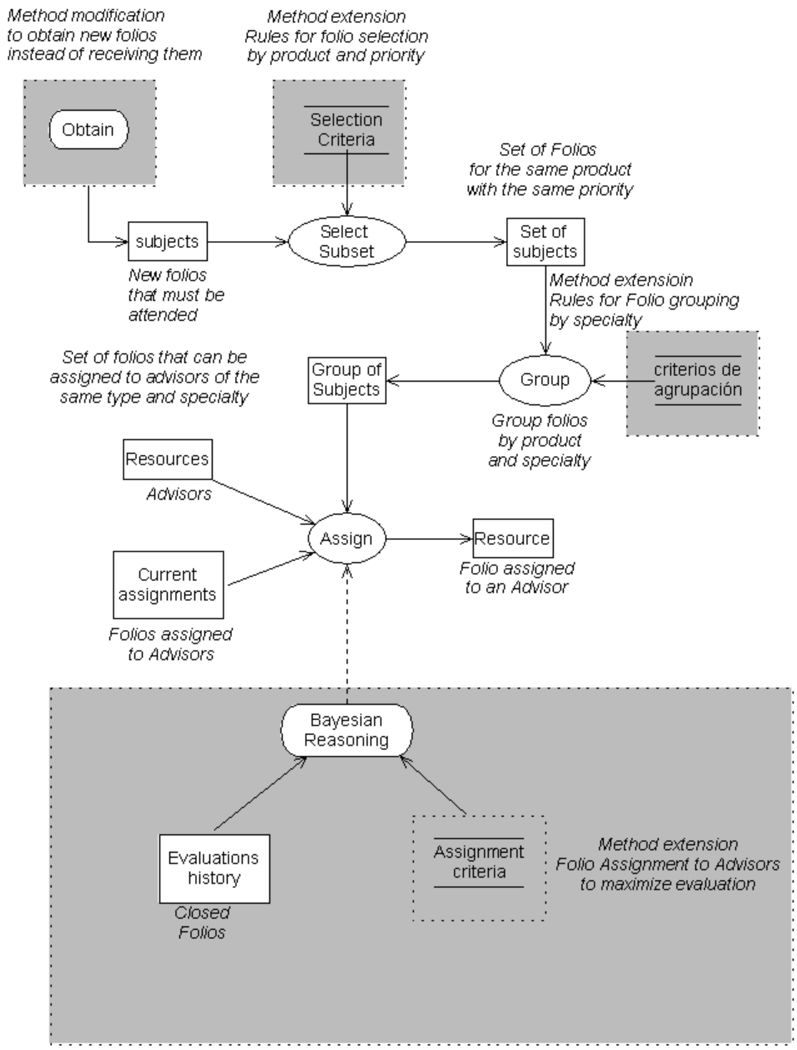


**Figure 6. Activity Diagram for the Assignation method with a learning algorithm.** Implementation details for the assignation inference. The shaded area shows the Bayesian reasoning implemented through BRF and the extensions made to the Common-KADS template for the assignation method.

The interaction is performed in an on-line fashion taking all kind of considerations in the system such as mixing information systems criteria and the specifying aspects of the Bayesian reasoning techniques.

The possibility of having access to the Bayesian reasoning techniques from a "user" agent is relevant, because the information system sets its goal to maximize the evaluation given by the customer that asked for the support.. Without the learning element, this would not be possible due to the fact that we do not have a static situation over which to evaluate an objective function. The conditions for the evaluation criteria are dynamic because they are modified with each folio evaluated by the customer.

The benefit of the incorporation of Bayesian reasoning into the information system is not limited to maximize the service evaluation. Also we eliminate human intervention since the autonomous agent does his job in an optimized way.

#### Learning and Inference using various Bayesian approaches

The Bayesian network used in this project is shown in figure 7. Its structure was modeled using the domain knowledge of human experts. It is composed of 23 nodes, from which 11 correspond to the available advisors to serve the Tourism Division of TCA, that is, they are the search goal in the network for the algorithm. The network handles only discrete variables. The network represents the relations between the concepts defined by the domain ontology (see also figure 3), that is, the product and area that motivates the service folio, folio type, customer type and the required level of service. The bottom nodes represent the advisors available in the case study.

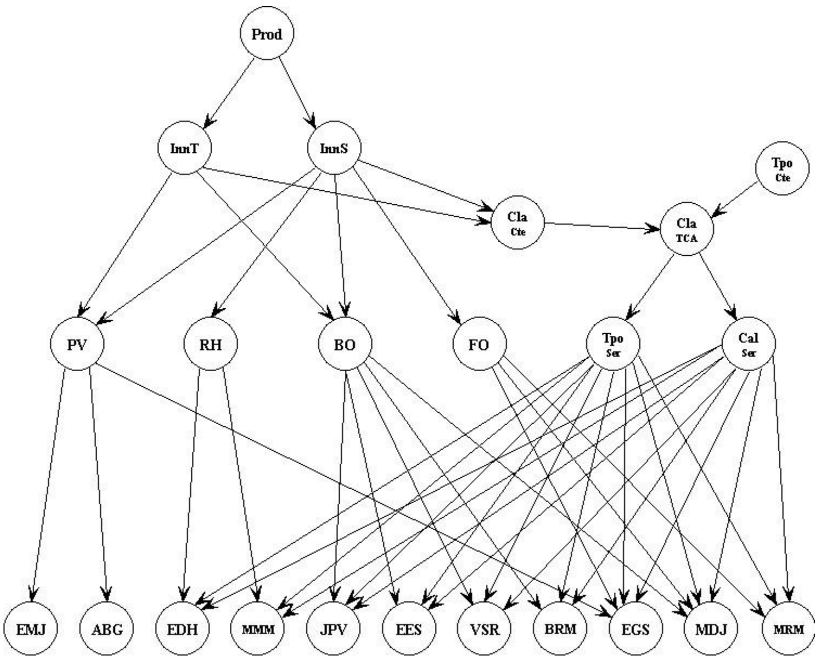


**Figure 7. Bayesian Network for Learning and Inference**

Because of the network topology, the biggest generated joint probability table has 64 entries. We have two nodes of rank 9 (Baase and Van Gelder, 2000), that is with 9 edges converging in the same direction (output). The joint probability distribution was learned by the autonomous agent from the historic data resulting from three years of operation.

We use 9,000 data records produced by 3 years of normal help desk system operation, 7,000 were used to learn the dependencies involved in the advisors assignation process and 2,000 were used for testing the generated assignations by the inference algorithm.

The Bayesian network structure was given as input to our algorithm for learning the model. It order to compare the performance of our algorithm with other implementations, the structure was also given as input to the Power Constructor[4] and Hugin Expert[5] Bayesian learning algorithms. The same network as well as the learned probabilities using our algorithm was given as input to the Java Bayes[6] inference algorithm.

BRF, Power Constructor and Hugin produced its own model using the same data set. Java Bayes was fed with the BRF learned model. Both Hugin Expert and Power Constructor have network structure learning capabilities. We did not use structure learning because our approach does not require that functionality as we model the complete network from domain knowledge in the implementation process.

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[4] Jie Cheng. (1998) Power Constructor, http://www.cs.ualberta.ca/~jcheng/bnpc.htm.

[5] Hugin Expert. (2004) Gasværksvej 5, DK 9000 Aalborg, Denmark, http://www.hugin.com.

[6] Fabio Gagliardi Cozman, (2001) Java Bayes. University of São Paulo, http://www-2.cs.cmu.edu/~javabayes/Home.

## ANALYSIS OF RESULTS

We found that the four reasoning algorithms worked correctly - the same way as the human expert that originally assigned advisors to service folios in the information system - between 93% and 96% of the test cases, that is, the reasoning algorithm used makes no difference in the assignation produced. This is expected, because despite of the fact that the four considered Bayesian learning and inference approaches use their own probability tables built from the same data set (except Java Bayes that uses the BRF generated tables), the network structure was given as input meaning that the join probability tables preserved the same structure in the four approaches, and then producing similar results. The implemented reasoning algorithm per se makes no difference in the outcomes.

Comparing the four frameworks, we found that both Power Constructor and Hugin Expert have GUI interface and the calls to the algorithms can be embedded in source code using proprietary Application Programmers Interfaces (APIs), neither have a middle tier. Java Bayes lacks a learning algorithm and the inference algorithm is embedded with the application using java code. They are well suited for deploying specific applications embedding the algorithms into the source code. In contrast, BRF do not need to be embedded into any source code, the reasoning algorithms contained in the repository are used through the middleware using SOAP (and then XML).

As it has been shown, the main differences between our approach and the other three considered are “framework differences”, the main strength of BRF is that it uses a multi tier approach with reasoning “services” implemented. We demonstrated that BRF provides the following advantages compared with other competing approaches:

- Having a middle tier managing user connections, encoding-decoding commands and data, acting as an ontology and Bayesian reasoning algorithms facilitator.
- Using a Bayesian reasoning techniques repository allowing for ontology definitions and on-line model updating.

The obtained results allow us to say that the implemented system using BRF helps to obtain evaluations as good as the obtained with the assignations made by the human expert. We can effectively substitute the human supervisor. The information system with Bayesian reasoning assigns the best advisors considering the results that provide evidence that the goal of obtaining the best evaluation and the shortest service time is met.

With the implementation of the assignation method using the Bayesian reasoning engine through BRF, we gave a packaged intelligence to the helpdesk system operating on-line. This result was expected and we can conclude that BRF is a useful environment that facilitates the development of information systems based on Bayesian reasoning.

The working environment offered by BRF, enhances the information system performance with the Bayesian reasoning engine by automating the following activities:

> Programming or choosing a Bayesian learning and inference algorithms, such as Hugin Expert or Power Constructor. Programming an interface between the information system and the BR algorithms, or embedding the algorithms into source code. Programming and choosing some method for coordination between the Bayesian reasoning techniques and the information system.

As we can see, if we want to implement Bayesian reasoning in an on-line information system without the BRF, we have a great amount of work to do. Also we must also take care of all the synchronization and control details in order to have the information system and the Bayesian reasoning algorithms interacting properly.

## CONCLUSIONS AND FUTURE WORK

BRF turns out to be a useful working environment for enhancing on-line information systems with Bayesian reasoning mechanisms. The design and implementation of BRF and its testing in a real-word, help-desk information system are the main contributions of this work. In order to delimit the scope of this project, BRF was developed considering only Bayesian reasoning, but the results obtained show that BRF can be extended to include other data mining techniques, that is, a “repository” of DM techniques can be used on-line by several information systems. The help-desk information system was properly implemented using Bayesian Reasoning through BRF according to the results obtained. As we delimit the interactions between the on-line information system and BRF with an autonomous agent by redefining the context of the implemented agent, the range of applications that can be solved with this approach using BRF is broad. Although the results are satisfactory, but there is plenty of work to be done. For future work, we will evolve BRF and implement more reasoning techniques. Also we have opened the following issues:

- Ontology management.
- Competitive evaluation of models for BRF to decide which DM technique to use in order to solve a given problem.
- Implementing additional DM techniques to have a central DM repository.

- Extending the approach by incorporating the concept of electronic institutions (Marc Esteva, 2003) and implementing other artificial intelligence techniques to allow and control complex interactions between information systems, data mining techniques and related ontologies, controlling the sequence of execution of business process, supervising its interactions and monitoring its performance.

**AKNOWLEDGEMENTS**

The authors acknowledge Grupo TCA, the Instituto Tecnológico y de Estudios Superiores de Monterrey, the Research and Graduate Programs Office and the Mechatronics Research Chair for their support for doing this research project.

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