Poznan University of Technology
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Master's thesis

DESIGN AND IMPLEMENTATION OF A COMPUTER SYSTEMS DIAGNOSIS TOOL USING BAYESIAN NETWORKS

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Chapter 1

Introduction

Diagnostic systems are becoming more popular and accurate. They help physicians as well as scientists perform differential diagnosis. The crucial part of every diagnostic system is its reasoning engine which relies on data. The input information comes from statistical data as well documented studies. Executed tests' reliability is critical in medicine as well as in computer science. There are no certain tests, however. To minimize false-positive impact of executed tests one can do them twice before supplying information to the diagnostic system. One of the possible implementations of reasoning engines are Bayesian networks. In this type of reasoning the information one supplies on the executed tests is final. The standard definition of *BNs* includes only two possible outcomes: *positive* and *negative*.

The following section describes Bayesian networks properties and impact. Reasoning example is given in chapter containing theoretical background.

1.1 Motivation

SOA architecture, among many other virtues, encourages functional software division into services. This enables business oriented partitioning, service cloning and on-the-fly service attach. While the system grows, however, it becomes more and more sophisticated. Software bugs might result in the failure of entire components. Fortunately, the vast connection net between services in a distributed processing system can be easily converted into a directed graph.

An example of such a system is the M^3 project (Metrics, Monitoring, Management) from IT-SOA. It is a set of modules for monitoring and management of SOA systems. Its main assumption is to keep the most up to date knowledge of the managed resources (components) and dependencies between them [1]. Thus the system provides the exact information on which system services have crashed. Going a step further one would want to know the *root causes* of failure, not only its symptoms. Bayesian networks are a perfect solution for this task. This is where a need for a specialised diagnosis service arose which would give the management system the ability to predict failure causes with appropriate probabilities.

The Bayesian Tool (*BT*) is intended to aid automated software and hardware diagnosis inside the M^3 framework [1]. File in a specific format should be sufficient to aid the diagnosis of a single hardware/software configuration. Many clients should be able to connect to the service via SOAP and REST simultaneously. A graphical client for this purpose using SOAP protocol

will be shipped with the *BT* software. The Bayesian server should provide extensive logging and algorithm selection.

1.2 Introduction to Bayesian networks

Bayesian network (*BN*) is one of the graph representations for modeling uncertainty. A Bayesian Network can depict a relationship between a disease and its symptoms, machine failure and its root causes or predict the most probable output passed through a noisy channel. In other words *BN*s are a structured, compact directed acyclic graphs (*DAG*s) which illustrate a problem that is too large or complex to be represented with tables or equations. Guaranteed consistency is Bayesian Networks' main strength among many other virtues such as the existence of efficient algorithms for computing probabilities without the need to compute the underlying probability distributions that would be computationally exacting. *BN*s are a ubiquitous tool for modeling and a framework for probabilistic calculations.

Bayesian network can be described by:

- a directed acyclic graph which is the structure of *BN* that enables one to reflect dependencies between components of the system in question
- conditional probability table (*CPT*) for each node with a positive input degree. *CPT*s describe the relation between a given node and its parents

Thanks to their simple interpretation, consistence and compact way of presenting probabilistic relations, Bayesian networks became a practical framework for commonsense reasoning under uncertainty and receive considerable attention in the fields of computer science, cognitive science, statistics and philosophy [2].

Bayesian Networks have many applications, apart from the ones mentioned above. These include the usage in computational biology, bio-informatics, medical diagnosis, document classification, image processing, image restoration and decision support systems.

One cannot ignore the immense importance of *BNs* in today's world filled with data and lacking appropriate tools as well as processing power.

1.3 The purpose and scope of work

Author of this work chose Bayesian networks as his Master's thesis subject mainly because it was strongly connected with his speciality - the *Intelligent Decision Support*. The important factor was also the growing popularity and ease of use of Bayesian networks in drawing accurate and complicated conclusions. The Bayesian tool project was done as a continuation of an earlier work in *IT-SOA* grant [3].

The purpose of work is to design and implement a computer systems diagnosis tool that provides a mechanism capable of stating the root cause of failure based on several observations. The symptoms might originate from sensors but the input mechanism is always a file in a text format.

The tool should enable the definition of relation between system components and sensors in a unique format (relation between parts that can be broken and tests that could be performed in order to identify the failure, along with appropriate conditional probability tables).

The implemented software should be able to build a Bayesian network given a file in unique format. Furthermore it should enable inference and visualisation of current network's state through a unified interface (API) as well as have a modular design and be compliant with *SOA* architecture.

1.4 Contents of this thesis

Master's thesis structure is as follows. In chapter 2 theoretical background is presented. One learns basic conditional probability notions in this part. This is followed by Bayes' theorem and the definition of d-separation test. Next, the Bayesian inference is explained.

Chapter 3.1 describes the system's architecture, especially the REST and SOAP methods. Bayes server operation description can be found in chapter 3.2 which includes the use of simple inference algorithm as well as the use of sampling algorithms.

Chapter 3.3 describes the communication language that is used by REST and SOAP. *BIF* format is described in this chapter as well.

Bayesian network and *CPTs* graphical representation is described in chapter 3.4.

Chapter 3.5 describes the technologies used in the implementation of Bayesian tool.

Chapter 3.6 is a classic manual for Bayes server and Bayes client.

Conclusions, information on C# code and Abbreviations that were used throughout this paper are described in chapters 4, 3.9 and 4 respectively.

Chapter 2

Theoretical background

This section presents concepts connected with probability that are essential for understanding the basis of Bayesian tool internals. In the first part few basic definitions, laws and rules are described. Section 2.3 deals with types of reasoning and section 2.4 with causality in Bayesian networks. Computations of the probability of exemplary events are shown in section 2.5. Section 2.7.2 is intended to explain how Bayesian networks work and provide an easy tutorial on reasoning.

2.1 Basic concepts and formulas

Formulas and notions presented in this section are needed to fully understand Bayesian networks operation. Some prior knowledge on probability is assumed. Especially the concepts of: random variable, probability distribution, discrete sample space and set theory should be familiar to the reader. Refer to book [4] for further explanation.

2.1.1 Conditional probabilities

The probability **P(X)** denotes the likelihood of a certain event while **P(X|Y)** refers to the probability of event X, given the occurrence of some other event Y. Consequently event X is conditional upon event Y. In a probabilistic situation the unconditioned probability P(X) has to be reduced to the outcomes where Y has a certain value (in this case is true) in order to create P(X|Y). Conditional probabilities are thoroughly described in book [5].

Joint probability distribution

The joint probability distribution is a multivariate distribution of random variables defined on the same probability space. The cumulative distribution for joint probability of two random variables is defined as: $F(x,y) = P(X < x, Y < y)$. In computer science one deals mostly with discrete variables. Simplifying, the probability of two events occurring at the same time ($X = x$, $Y = y$) or in other words the probability of two components being in certain states (x, y) will be: **P(X,Y)**, also depicted as $P(X \cap Y)$.

Marginal probability

Given the joint probabilities of X and Y the marginal probability can be computed by summing joint probabilities over X or Y. For discrete random variables, the marginal function can be written as: $P(X = x)$ and the probability (over Y) is the sum of probabilities $P(X = x, Y = y_1)$, P(X=x, Y=y_2) ... $P(X = x, Y = y_n)$. The formula sums probabilities of all possible situations where the main event is constant (X is in a certain state) and the event one sums over (in this case Y) is given all other possible values.

Joint distribution: P(X,Y)				
	Y=y1	Y=y2	Y=y3	Marginal probability
X=x1	0.693	0.09	0.04	0.823
X=x2	0.007	0.01	0.16	0.177
Marginal probability	0.700	0.100	0.200	1

joint probability

marginal probability

FIGURE 2.1: Marginal distribution [6].

Conditional probability:

$$P(X \mid Y) = \frac{P(X \cap Y)}{P(Y)} \tag{2.1}$$

Conditional probability $P(X \mid Y)$ can be computed by dividing the joint probability of events X and Y by the marginal probability $P(Y)$.

2.1.2 Sum rule, product rule

Sum rule

The overall probability of an event X is the sum of all joint probability distributions connected with this event:

$$P(X) = \sum_{Y} P(X,Y); \qquad constraints: P(X) \geqslant 0 \wedge \sum_{X} P(X) = 1 \tag{2.2}$$

In other words it is the marginal probability over all events Y_i that X depends on.

Product rule

The joint probability of an events X and Y is the product of a conditional probability and a probability of the dependent event:

$$P(X,Y) = P(Y|X) * P(X) = P(X|Y) * P(Y) \tag{2.3}$$

$$constraints: P(X) \geqslant 0 \wedge \sum_{X} P(X) = 1$$

Combining the above two one gets:

$$P(X) = \sum_{Y} P(X|Y) * P(Y) \tag{2.4}$$

2.1.3 Bayes' theorem

Bayes theorem is used to calculate *inverse probability*, that is: knowing the conditional probability P(Y|X) one can compute the probability P(X|Y). The formula expresses the posterior probability that is expressed on some prior knowledge. In most cases hypothesis H is drawn after some evidence E is observed:

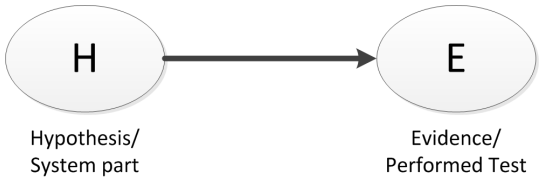


FIGURE 2.2: Hypothesis and evidence

$$P(H|E) = \frac{P(E|H) * P(H)}{P(E)} \tag{2.5}$$

where:
P(H|E) is the posterior probability that the hypothesis is true
P(E|H) is the prior knowledge
The formula 2.5 basically summarizes all theory behind Bayesian tool internals.

2.2 Bayesian networks

Bayesian networks are *DAGs* that represent a probabilistic situation. Some nodes are designated as *parts* and some as *tests*. Middle nodes are possible as well - these are nodes that have both: parents and children in the *DAG*. Test nodes can be executed resulting in a probability update. Positive or negative outcome of the execution is possible while node's probabilities are updated according to the result. The reasoning process is described thoroughly in section 2.7. Benefits of using *BNs* as a reasoning engine are described in Chapter 1.

2.3 Types of reasoning in Bayesian networks

There are four main types of reasoning in Bayesian networks [7]:

- causal reasoning ($H \rightarrow E$)
- diagnostic reasoning / evidential reasoning ($H \leftarrow E$)
- inter-causal reasoning
- mixed type reasoning

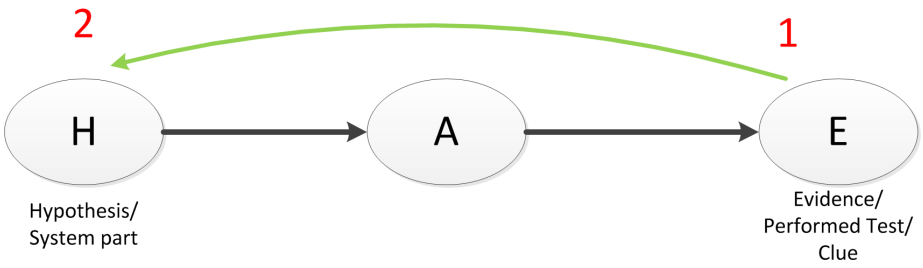


FIGURE 2.3: Diagnostic reasoning

In diagnostic reasoning with the arrival of clue E one wants to calculate the probability of hypothesis H being true. In other words - one sees the evidence and looks for most probable causes, e.g. a diagnostic light starts flashing in your car's dashboard and you want to know which part of the car is broken.

2.4 Causal and evidential reasoning

Causal and evidential are most common types of reasoning. This section describes both kinds, however thanks to evidential reasoning Bayesian networks became the ubiquitous tool for differential diagnosis even though this type requires much more computational power than causal reasoning. On the other hand causality is the fundamental part of Bayesian networks and without it there would be no reasoning.

2.4.1 Definitions

Evidential reasoning is deriving causes from effects: given an observed phenomenon, one tries to explain it by the presence of other phenomena. *Causal reasoning* concentrates on deriving effects from causes: given an observed (or hypothesized) phenomenon, one is induced by it to expect the presence of other phenomena, which have the role of its effects.

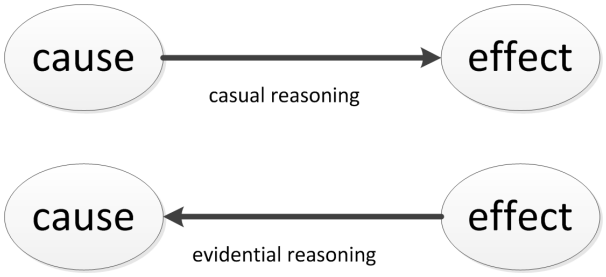


FIGURE 2.4: Causal and evidential reasoning

2.4.2 Causality in Bayesian networks

Bayesian networks represent causality by their structure - arcs follow direction of causal processes. Prior to constructing *DAG* one need to analise the problem to infer such dependencies. There are some studies focused on automating this process and inferring such data from databases

as described in [2]. In many practical applications one can interpret network edges as signifying direct causal influences with the exception of artificial nodes created only to improve calculations and accuracy. Such variables, however, are beyond the scope of this work.

One has to remember that causal networks are always Bayesian and Bayesian networks are not always causal. Only causal networks are capable of updating probabilities based on interventions, as opposed to observations in Bayesian.

As it was mentioned earlier causality is represented by arcs in *BN*. During the construction of such a network one has to be careful not to inverse conditional probabilities (arcs)
as $P(A|B) \neq P(B|A)$.

2.5 Basic assumptions in Bayesian networks

Knowledge in Bayesian networks is represented in the form of direct connections between probabilistic variables. One needs to fix the conditional probability of a given variable and their direct parents. All other relations can be computed from these simple dependencies.

2.5.1 Independence of variables based on graph structure

Nodes which are not directly connected in the DAG represent independent variables. It means that when there is no direct path between two nodes in Bayesian network, variables represented by these two not-connected nodes are independent. Consequently arcs in DAG represent relation of direct dependence between two variables and the strength of this dependence is scaled in the form of conditional probability.

Independence example

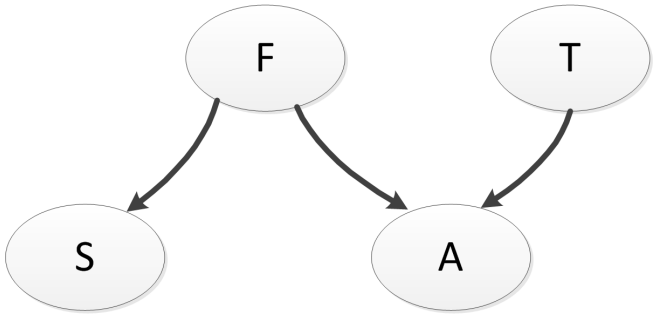


FIGURE 2.5: Independence example

In the above figure variables S and T are independent as there is no connection from T to S.

2.5.2 Probability P(X) of a given node

The probability of a given node depends only on its parents which “hide” preceding nodes and their influence. In other words every variable in the structure is assumed to become independent of its non-descendants once its parents are known.

Example

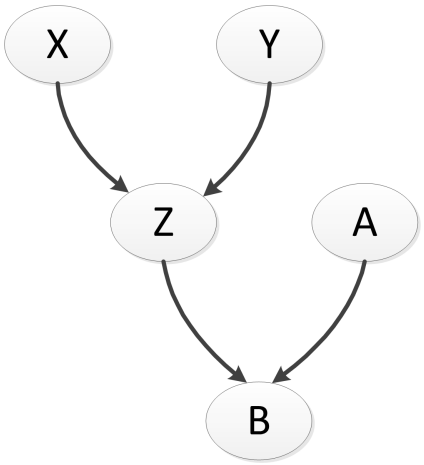


FIGURE 2.6: P(X) of a given node

In the above figure the probability P(B) can computed as follows:

$$P(B) = P(B|Z,A) * P(Z) * P(A) + P(B|\neg Z,A) * P(\neg Z) * P(A) + \tag{2.6}$$

$$+P(B|Z,\neg A) * P(Z) * P(\neg A) + P(B|\neg Z,\neg A) * P(\neg Z) * P(\neg A)$$

2.5.3 Other properties of Bayesian networks

Other exemplary conditional probabilities can be computed based on the example in the figure 2.6:

$$P(B|A) = P(B|A,Z) * P(Z) + P(B|A,\neg Z) * P(\neg Z) \tag{2.7}$$

$$P(B|X) = P(B|Z) * P(Z) + P(B|\neg Z) * P(\neg Z) \tag{2.8}$$

Joint probability of events

The joint probability $P(X,Y,Z,A,B)$ can be computed as follows:

$$P(X,Y,Z,A,B) = P(B|Z,A) * P(Z|X,Y) * P(X) * P(Y) * P(A) \tag{2.9}$$

The formula represents exactly the Bayesian network structure from figure 2.6.

Joint probability of selected events

Joint probability of *selected events* is computed by taking all the events that are irrelevant to the query, making all boolean combinations of these events and summing the joint probabilities with

these combinations:

$$P(X,Z,A) = P(X,Y,Z,A,B) + P(X,Y,Z,A,\neg B) + P(X,\neg Y,Z,A,B) + P(X,\neg Y,Z,A,\neg B) \quad (2.10)$$

Y	B
1	1
1	0
0	1
0	0

Other examples

Other exemplary Bayesian networks are presented in figure 2.7 along with some computed joint probabilities:

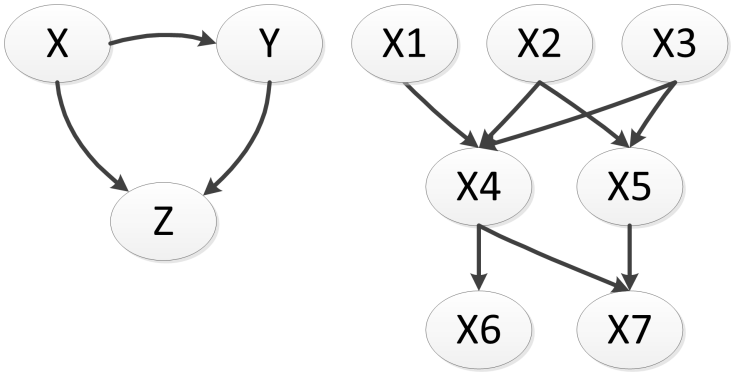


FIGURE 2.7: Bayesian exemplary networks

$$P(X,Y,Z) = P(Z|X,Y) * P(Y|X) * P(X) \quad (2.11)$$

$$P(X_1,X_2,...,X_7) = P(X_1) * P(X_2) * P(X_3) * P(X_4|X_1,X_2,X_3) * P(X_5|X_2,X_3) * \quad (2.12)$$

$$* P(X_6|X_4) * P(X_7|X_4,X_5)$$

2.5.4 Empirical priors in Bayesian networks

It is necessary to use empirical priors in Bayesian networks so that computations are based on acquired data rather that on constructor's subjective beliefs. Priors which aren't based on data are called uninformative. One can even use flat priors if no knowledge is available [8].

Frequentists use statistical analysis to draw conclusions from data. Their analysis is usually inferior as it is just a few summary statistics of prior probabilities when Bayesians tend to present the actual posterior probability distribution.

2.6 D-separation

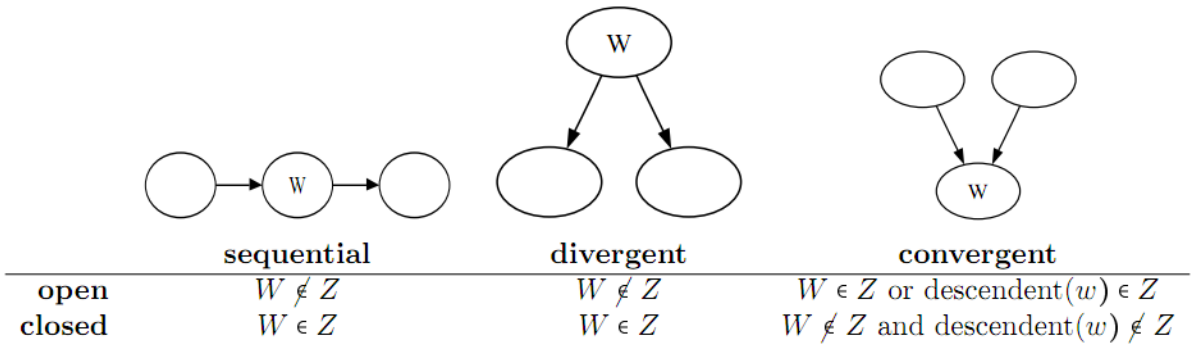
D-separation test is used to determine dependency of groups of variables. According to this test variables X and Y are guaranteed to be independent given the set of variables Z if *every* path between X and Y is blocked by Z. That is every path between X and Y can be labelled "closed" given Z according to the rules described below.

Test is inconclusive if at least one path stays "open". In such case one cannot claim independence but also cannot claim dependence. If X and Y are not *d-separated*, they are called *d-connected*. The designation $X \perp\!\!\!\perp Y \,|\, Z$ means X is independent of Y given Z (X,Y and Z are set of variables).

According to paper [2] one only needs the Markovian assumptions to determine the variable dependency. The appeal to notion of causality is not necessary here. The full d-separation test gives the precise conditions under which a path between two variables is blocked.

2.6.1 D-separation rules

The figure depicted below describes rules that decide whether the specific node in the path is *open* or *closed*. One *closed* node in the path makes the whole route *closed*.



	sequential	divergent	convergent
open	$W \notin Z$	$W \notin Z$	$W \in Z$ or descendent$(w) \in Z$
closed	$W \in Z$	$W \in Z$	$W \notin Z$ and descendent$(w) \notin Z$

FIGURE 2.8: d-separation open and closed path rules [9]

D-separation example

The following example will show how rules from section 2.6 are used in practice.

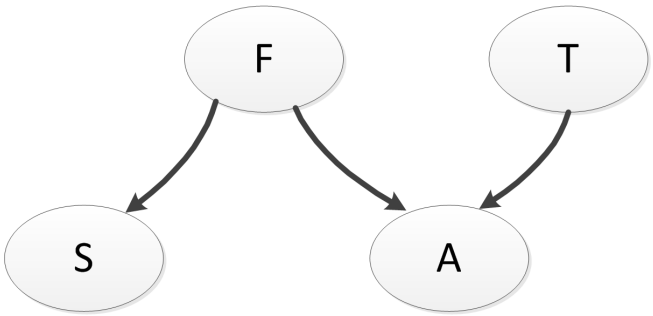


FIGURE 2.9: d-separation example

In this test two separations will be checked:

- $S \perp\!\!\!\perp T \,|\, F$
- $S \perp\!\!\!\perp T \,|\, A$

In the first case the separation set is {F}. One has to check all nodes in the path between S and T. The path is closed if one node closes it. Reasoning is done with the help of rules in section 2.6.1. $F \in \{F\} \rightarrow divergant \rightarrow closed$. So the only available path between S and T is closed, hence variable S and T *is independent* given {F}.

In the second example the separation set is {A}. One has to check if node A blocks the path. $A \in \{A\} \rightarrow convergant \rightarrow open$. So the node A does not block the path and it stays open. F∈{A}→divergant→open. The path still stays open and there are no further nodes to check. As described in 2.6 *one cannot claim independence but also cannot claim dependence*. The test is inconclusive as to $S \perp\!\!\!\perp T \,|\, A$.

2.7 Bayesian inference

Bayesian inference opposes statistical inference where one draws conclusions from statistical samples. In *BI* different kinds of evidence (or observations) are used to update previously calculated probability. However, *BI* uses ***prior*** estimate of the degree of confidence in the hypothesis which most often is just a statistical probability of failure of a particular part. In other words Bayesian inference uses a prior probability over hypotheses to determine the probability of a particular hypothesis given some observed evidence.

Bayesian inference extends probability usage to the areas where one deals with uncertainty not only repeatability. This is possible thanks to Bayesian interpretation of probability, which is distinct from other interpretations of probability as it permits the attribution of probabilities to events that are not random, but simply unknown [10].

During the reasoning process using Bayesian inference the evidence accumulates and the degree of confidence in a hypothesis ought to change. With enough evidence, the degree of confidence should become either very high or very low. Thus, *BI* can discriminate between conflicting hypotheses.

Bayesian inference uses an estimate of the degree of confidence (the *prior* probability) in a hypothesis before any evidence has been observed which results in a form of inductive bias. Results will be biased to the *a-priori* notions which affect prior $P(X)$ node probabilities, *CPTs* and consequently the whole reasoning process.

2.7.1 Inference algorithms

Inference algorithms fall into two main categories:

- exact inference algorithms
  - based on elimination
  - based on conditioning

- approximation inference algorithms

Exact algorithms are structure-based and thus exponentially dependant on the network *treewidth*, which is a graph-theoretic parameter that measures the resemblance of a graph to a tree structure [2]. *Approximation algorithms* reduce the inference problem to a constrained optimization problem and are generally independant of treewidth. *Loopy belief propagation* is a common algorithm nowadays for handling graphs with high *treewidth* [2].

2.7.2 Bayesian inference example

This example is based on computer failure diagnostics. There are two possible hardware failures - a RAM failure where part of the chip is broken and stores inaccurate data and a CPU failure when the processor overheats and causes the whole system to crash. One can see two possible evidences - a Blue Screen of Death (*BOD*) or a system hang. Each of the causes can result in *BOD* or hang. The overall structure of the network is presented in figure 2.10 and probabilities as well as *CPTs* are presented in figure 2.11.

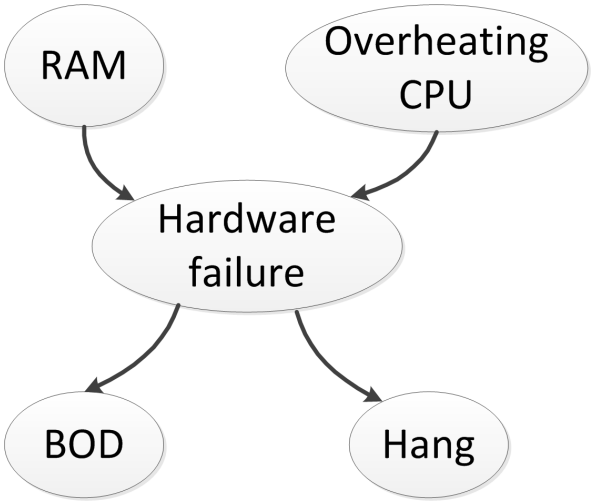


FIGURE 2.10: Inference example network

Example network with node probabilities and CPTs

Figure 2.11 presents the Bayesian network along with individual *CPTs*. This network is used throughout the example reasoning process. All probabilities depicted in the figure 2.11 are prior probabilities.

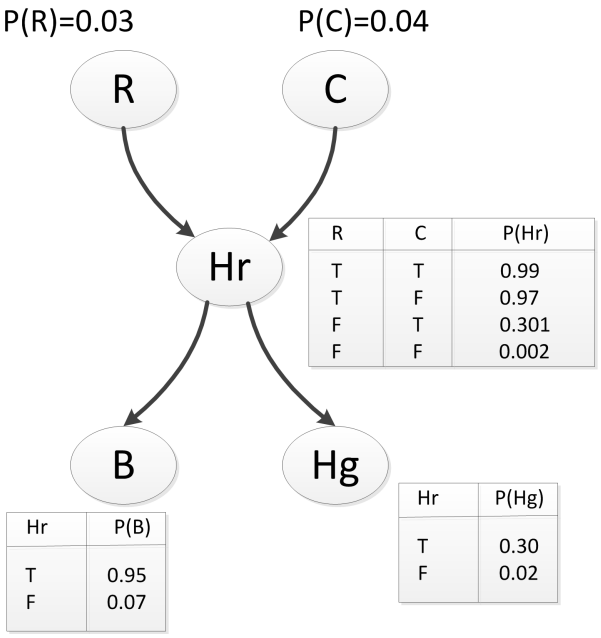


FIGURE 2.11: Inference example network with CPTs

Reasoning

The reasoning process is an example of **diagnostic reasoning** as one infers cause (hypothesis) probability from evidence. However, some causal reasoning has to be done first in order to compute required probabilities - P(B) and P(B|R).

Evidence nodes are placed on the bottom and cause nodes on the top. The whole process consists of two parts:

- inference part
  where one infers probability from the new data that has been provided. In this case the new fact is that there has been a *BOD*.

- node update part
  where one updates all probability values affected by the change of probability of the cause nodes.

Following the top-bottom logic: the inference part is bottom-top and the update part is top-bottom in the network representation from figure 2.11.

In this example *BOD* test will be "executed" and the result will come out to be positive. Next the posterior probability of RAM failure and CPU failure will be inferred. One has to update all probability values affected by this change - P(Hr), P(B), P(Hg).

In the first iteration these probabilities can be taken from "statistical" data or computed in the process of causal reasoning. The latter possibility will be shown in this example.

The overall process of inference is to compute the P(R|B) probability and substitute: **posterior P(R) = P(R|B)**. Then one has to compute P(C|B) and substitute: posterior P(C)=P(C|B); In the end the new P(Hr), P(B), P(Hg) probabilities are computed.

Computations

The main goal is to compute P(R|B):

$$P(R|B) = \frac{P(B|R) * P(R)}{P(B)} \tag{2.13}$$

In order to do that one needs to compute:

- P(B|R)
- P(Hr|R)
- P(B)
- P(Hr)
- P(R|B)

Causal reasoning part

To compute the conditional probability P(B|R) one needs:

$$P(B|R) = \frac{P(B,R)}{P(R)} = \frac{P(B|Hr) * P(Hr|R) * P(R) + P(B|\neg Hr) * P(\neg Hr|R) * P(R)}{P(R)} = \tag{2.14}$$

$$= P(B|Hr) * P(Hr|R) + P(B|\neg Hr) * P(\neg Hr|R)$$

where:

$$P(Hr|R) = P(Hr|R,C) * P(C) + P(Hr|R,\neg C) * P(\neg C) = 0.99 * 0.04 + 0.97 * 0.96 = 0.9708 \tag{2.15}$$

$$P(\neg Hr|R) = 1 - P(Hr|R) = 0.0292 \tag{2.16}$$

$$P(B) = P(B|Hr) * P(Hr) + P(B|\neg Hr) * P(\neg Hr) \tag{2.17}$$

where:

$$P(Hr) \quad = \quad P(Hr|R,C) * P(R) * P(C) + P(Hr|R,\neg C) * P(R) * P(\neg C) + \tag{2.18}$$

$$+P(Hr|\neg R,C) * P(\neg R) * P(C) + P(Hr|\neg R,\neg C) * P(\neg R) * P(\neg C) =$$

$$= 0.99 * 0.03 * 0.04 + 0.97 * 0.03 * 0.96 + 0.301 * 0.97 * 0.04 + 0.002 * 0.97 * 0.96 = 0.0426652$$

$$P(B) = 0.95 * 0.0426652 + 0.07 * 0.9573348 = 0.107545 \tag{2.19}$$

$$P(B|R) = P(B|Hr) * P(Hr|R) + P(B|\neg Hr) * P(\neg Hr|R) = \tag{2.20}$$

$$= 0.95 * 0.9708 + 0.07 * 0.0292 = 0.924394$$

So one has:

$$P(Hr) = 0.0426652; P(B) = 0.107545; P(Hr|R) = 0.9708; P(B|R) = 0.924394 \tag{2.21}$$

Diagnostic reasoning part

$$P(R|B) = \frac{P(B|R) * P(R)}{P(B)} = \frac{0.924394 * 0.03}{0.107545} = 0.257862476 \tag{2.22}$$

$$posterior \quad P(R) = P(R|B) = 0.257862476 \tag{2.23}$$

Computing posterior probability P(C)

In this section the probability P(C|B) will computed and the following substitution will be made: posterior P(C) = P(C|B)

$$P(C|B) = \frac{P(B|C) * P(C)}{P(B)} \tag{2.24}$$

where:

$$P(B|C) = \frac{P(B,C)}{P(C)} = \frac{P(B|Hr) * P(Hr|C) * P(C) + P(B|\neg Hr) * P(\neg Hr|C) * P(C)}{P(C)} = \tag{2.25}$$

$$= P(B|Hr) * P(Hr|C) + P(B|\neg Hr) * P(\neg Hr|C)$$

where:

$$P(Hr|C) = P(Hr|C,R) * P(R) + P(Hr|C,\neg R) * P(\neg R) = 0.99 * 0.03 + 0.301 * 0.97 = 0.32167 \tag{2.26}$$

$$P(\neg Hr|C) = 0.67833 \tag{2.27}$$

So the probability:

$$P(B|C) = 0.95 * 0.32167 + 0.07 * 0.6783 = 0.35307 \tag{2.28}$$

And the probability:

$$P(C|B) = \frac{P(B|C) * P(C)}{P(B)} = \frac{0.35307 * 0.04}{0.10754} = 0.13133 \tag{2.29}$$

$$posterior \quad P(C) = P(C|B) = 0.13133 \tag{2.30}$$

Probability update part

Probability update is the second part of reasoning as described in 2.7.2. This phase is also called "*probability propagation*". One has to compute all posterior probabilities of the "affected" nodes - that is nodes that are connected with variables updated in the first part (*causal reasoning*).

$$posterior \quad P(Hr) = P(Hr|R,C) * P(R) * P(C) + P(Hr|R,\neg C) * P(R) * P(\neg C) + \tag{2.31}$$

$$+P(Hr|\neg R,C) * P(\neg R) * P(C) + P(Hr|\neg R,\neg C) * P(\neg R) * P(\neg C) =$$

$$= 0.99 * 0.258 * 0.131 + 0.97 * 0.258 * 0.869 + 0.301 * 0.742 * 0.131 + 0.002 * 0.742 * 0.869 = 0.28148$$

The propagation to *"Hang"* node is dependant on the definition of the system. If it can have a BOD and then hang there is point in propagating the probability. If the symptoms are excluding then there is no point in propagating the probability. This example assumes that both symptoms could have occurred at the same time but information on only one of them is available.

$$posterior \quad P(Hg) = P(Hg|Hr) * P(Hr) + P(Hg|\neg Hr) * P(\neg Hr) = \tag{2.32}$$

$$= 0.30 * 0.28148 + 0.02 * 0.71852 = 0.0988$$

Conclusions

The table below presents prior and posterior probabilities of all the nodes in the network:

	prior	posterior
P(R)	0.03	0.2579
P(C)	0.04	0.13133
P(Hr)	0.0426652	0.28148
P(B)	0.107545	**1.0000**
P(Hg)	0.03195	0.0988

The prior P(Hg) comes from:

$$prior \quad P(Hg) = P(Hg|Hr) * P(Hr) + P(Hg|\neg Hr) * P(\neg Hr) = \tag{2.33}$$

$$= 0.30 * 0.0427 + 0.02 * 0.957 = 0.03195$$

The probability of posterior P(B) equals **1.0** because of the test that was performed. This information was then inferred to the variables representing failure causes. The certainty of P(B) actually enables us to substitute: posterior P(R) = P(R|B) and posterior P(C) = P(R|C).

One has to treat posterior probabilities as problem investigation. The occurrence of BOD has increased the probability of hardware failure from 0.04 to 0.28. In this example it would appear to be reasonable to assume that the hardware failure is true. That is not the case however as the probability P(B|Hr)=0.95. So not all hardware failures cause BOD.

One can see from the computed data that the probability of RAM failure rises much more than the probability of CPU overheat. That is because RAM causes hardware failures more frequently when it is broken - this information comes from the conditional probability table of Hr $[P(Hr|R,\neg C) = 0.97$ while the probability of $P(Hr|\neg R,C) = 0.301]$. The key element is that the probability of both nodes R and C has to rise at all after the positive execution of BOD test.

The probability of system hang does not rise much as P(Hg|Hr) = 0.30 is rather low.

After the update the network looks as follows:

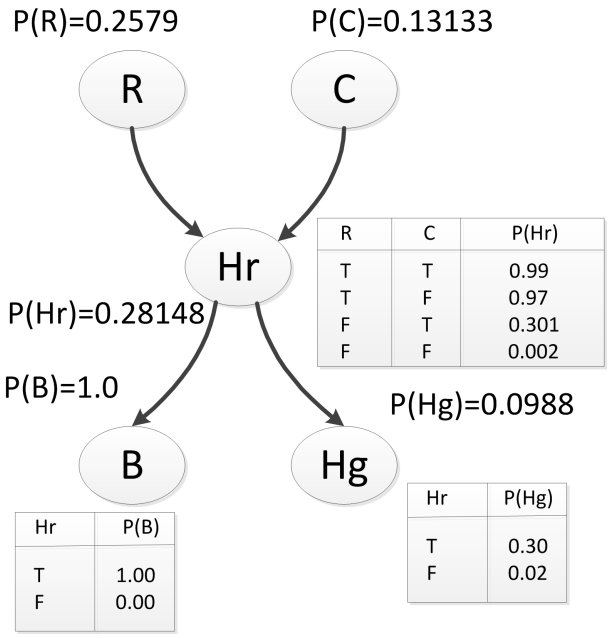


FIGURE 2.12: Inference example network with CPTs after update of probabilities

2.8 Conditional probability table

The two-dimensional conditional probability table of variables X and Y describes the probabilities of $P(\neg Y|\neg X), P(Y|\neg X), P(\neg Y|X), P(Y|X)$. The conditional probability table $A_{Y|X}$ describes the probability of Y given X.

		Y	
		0	1
X	0	P(¬Y|¬X)	P(Y|¬X)
	1	P(¬Y| X)	P(Y| X)

FIGURE 2.13: Conditional probability table

Conditional probability table is a right stochastic matrix which means that each row consists of non-negative real numbers and is summing to 1.

2.9 Markov chains

Markov chains are mathematical systems undergoing constant transitions from one state to another. There exists a finite number of possible states. The theory behind Markov chains is the base for understanding sampling algorithms in Bayesian networks.

2.9.1 Formal definition

Markov chain is a *discrete-time* random process, where *discrete-time* means that the sampling process occurs at non-continuous times and so results in discrete-time samples. In other words it is a *chain of events* at specific moments in time. [Continuous Markov-chain is not described here].

Hence a Markov chain is a sequence of random variables $X_1, X_2, X_3 ... X_n$ that have so called *"Markov property"* which means that future and past states are independant.

Markov chains are often described by a directed graph or a transition probability table P. States set is specified as $S = \{S_1, S_2, ..., S_n\}$. Markov chain needs to have a finite number of states.

$$P(X_{n+1} = x | X_1 = x_1, X_2 = x_2, ... X_n = x_n) = P(X_{n+1} = x | X_n = x_n) \tag{2.34}$$

Equation 2.34 means that the next state of the Markov chain depends **only** on the current state and transition probability table connected with this state.

Describing Markov chains informally one observes the **random** walk of a pebble between a finite number of states and the walk is determined by probability values of going to certain states that are bound to each state. X_0 is the initial distribution according to which the pebble is placed in the network in the beginning.

Markov chain transition probability table

Transition probability table is a finite n×n transition probability matrix. $P = [p_{ij}]$ is a matrix where p_{ij} is the transition probability of going from state i to state j.

For the Markov chain with 2 states {0,1} the transition probability table A is given as:

	0	1
0	0.306	0.694
1	0.282	0.718

The probability of changing state to 1 while in 0 state is 0.694 while the probability of staying in 0 equals 0.306.

The transition probability table is a right stochastic matrix so the sum of the probabilities of the arcs outgoing from a vertex i sum up to 1, i.e. $\sum_j p_{ij} = 1$ It is easy to change the meaning of the matrix from Conditional probability table to transition probability treating variable values as separate states. This operation is trivial for binary variables.

Markov chain directed graph

The directed graph for Markov chain described in 2.9.1 is as follows:

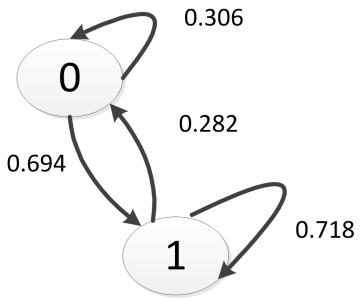


FIGURE 2.14: Conditional probability table

Periodicity, Recurrence, Ergodicity

Markov chains' states have certain properties. The ones mentioned below are crucial for understanding how stationary Markov chains (section 2.9.2) work.

- **Periodicity** - if a state i has a **period k** then any return to state i has to occur in k time steps
- **Recurrence** - probability of returning to state i
  - *transient* - there is a non-zero probability that one will never return to i
  - *recurrent* - state i has finite hitting time with probability 1
    - *positive recurrent* - hitting_probability = 1 with finite time
    - *null recurrent* - otherwise
- **Ergodicity** - state i is ergodic when it is aperiodic and positive recurrent

2.9.2 Stationary Markov chains (Time-homogeneous Markov chains)

Stationary Markov chains are defined as follows:

$$P(X_{n+1} = x|X_n = y) = P(X_n = x|X_{n-1} = y) \tag{2.35}$$

for all n.

A Markov chain is *stationary* when the probability of the transition is independent of n. In other words every stationary chain has a "limit" distribution $\pi = (\pi_1, ..., \pi_n)$ that the distributions in following states X_i of Markov chain converge to.

A Markov chain is convergent when:

- its graph is strongly connected
- it is ergodic (that is aperiodic and positive recurrent)

If the first condition was not met the graph could have two "sinks" that the Markov chain could converge to. If the second condition was not met the chain's distributions would loop indefinitely.

After t-steps in Markov chain one has:

$$X_t = X_{t-1} * P = X_0 * P^t \tag{2.36}$$

Stationary Markovian chain is convergent when $t \to \infty$:

$$\lim_{t\to\infty} p^t = P^\infty \tag{2.37}$$

where:

$$P^\infty = \begin{bmatrix} \pi_1 .....\pi_n \\ \pi_1 .....\pi_n \\ \pi_1 .....\pi_n \end{bmatrix} \tag{2.38}$$

2.10 GIBBS sampling

The purpose of a GIBBS sampler is to approximate the joint distribution. It is a *randomized* algorithm widely used in inference, especially in Bayesian networks. GIBBS is an example of Markov chain Monte Carlo algorithm.

As a result of its randomized nature it produces different results with every run but it was shown [11] that with enough samples it converges to the sought-after joint distribution thanks to stationary Markov chains [12].

One uses GIBBS sampling when the joint distribution is not known explicitly or is difficult to sample from directly, but the conditional distributions are easy to get (sample from).

2.10.1 From sequence of samples to joint distribution

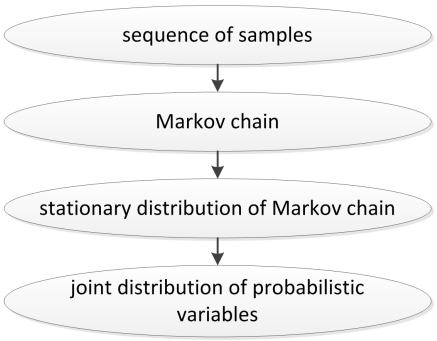


FIGURE 2.15: Sequence of samples to joint distribution in GIBBS

It can be shown that the sequence of samples constitutes a Markov chain, and the stationary distribution (refer to: 2.9.2) of that Markov chain is just the sought-after joint distribution of the probability the sampling was done for.

2.10.2 Sampling algorithm operation

A sampling algorithm runs in a for loop which can be limited by number of cycles (*samplingCount* property) or some other stop condition. A Gibbs sampler is a Markov chain on $(X_1, \ldots, X_n)$. For convenience of notation, one can denote the set $(X_1, \ldots, X_{i-1}, X_{i+1}, \ldots, X_n)$ as $X(-i)$, the set of evidence variables as $e = (e_1, ..., e_m)$ and the conditional probability as $P(X_1, \ldots, X_n | e_1, \ldots, e_m)$. To create a Gibbs sampler:

1. Initialize:

   a) Instantiate X_i to one of its possible values x_i, $1 \leq i \leq n$
   that is: choose nodes and give them values according to conditional probability:
   for $P(X|Y = y_1, Z = z_1)$ choose $Y = y_1$ and $Z = z_1$

   b) Let $x(0) = (x_1, \ldots, x_n)$
   that is instantiate the Markov chain with the chosen values:
   for $P(X|Y = y_1, Z = z_1)$ choose $x(0) = (Y = y_1, Z = z_1)$

2. For loop with a stop condition (preferably *samplingCount* property):

   a) Pick an index i, $1 \leq i \leq n$ uniformly at random
   that is: choose one of the variables Y or Z e.g. with Math.random() function.

   b) Sample x_i from $P(X_i | x_{(-i)}^{(t-1)}, e)$
   one samples the chosen variable given all other variables (without variable X_i):
   - other conditional variables from $P(X|Y = y_1, Z = z_1)$ with values [t-1]
   - all of the rest of the nodes with 'true' value
   that is:

      i. if one chose Y:

sample from $P(Y|Z = [value]_{t-1}, X = true)$

i. if one chose Z:

sample from $P(Z|Y = [value]_{t-1}, X = true)$

c) Let $x(t) = (x(-i), x_i)$

i. if one chose Y:

let $X(t) = (Y = [value]_t, Z = [value]_{t-1})$

i. if one chose Z:

let $X(t) = (Y = [value]_{t-1}, Z = [value]_t)$

Chapter 3

Bayesian diagnostic tool

The result of the Bayesian project is a diagnosis tool that is an integral part of *IT-SOA* framework [3]. It consists of the Bayesian server and client communicating with the help of SOAP methods. Its architecture is compliant with *SOA* principles where each part of the software is a separate module.

The Bayes server accepts commands in REST and SOAP interfaces from multiple users at once remembering their reasoning history.

Prior to using Bayesian tool a Bayesian network has to be created. *BS* accepts multiple network formats as input - its internal format *GRAPH* and *WEKA's BIF* format. Upon successful *BIF* import the network is automatically converted to *GRAPH*. All data formats are described later on in the chapter.

All communication between the server and clients is done using self-describing XMLs which are presented in section 3.3. Current reasoning state for a certain user can be viewed simply by entering appropriate address in a web browser (i.e. using correct REST method). Bayes server saves every request and provides a convenient console as well as text-file log.

To successfully use the Bayesian client one has to obey domain security rules which are endorsed by *Microsoft's Silverlight*. These are described in 3.1.5. One can implement its own tool to work with Bayesian server but a strict order of method calls is required (section 3.1.6).

Bayesian server implements an exact algorithm for reasoning as well as many sampling algorithms taken from *SMILE* library. The degradation of accuracy between the exact algorithm and sampling algorithms is inconspicuous. Apart from reasoning *BS* offers best *VOI* algorithms - the concept of VOI tests is described in the manual.

The graphical interface of Bayesian client is extremely easy to use. It offers eye-catching controls and is ergonomic in usage. Click count ratio was taken as seriously as possible.

Chapter overview This chapter presents the system architecture, deals with the basic Bayesian tool operation and describes the technologies used. Section 3.3 deals with communication languages and section 3.6 is the Bayesian tool manual. In the end conclusions from the entire project are drawn.

3.1 System architecture

This section deals with system components and communication methods. Service specification along with REST and SOAP methods description is presented afterwards. Specific method order which is presented in section 3.1.6 is required for successful reasoning with Bayesian tool. In the end of the section *Silverlight's* access policy is mentioned which enables Bayesian client operation.

3.1.1 System components

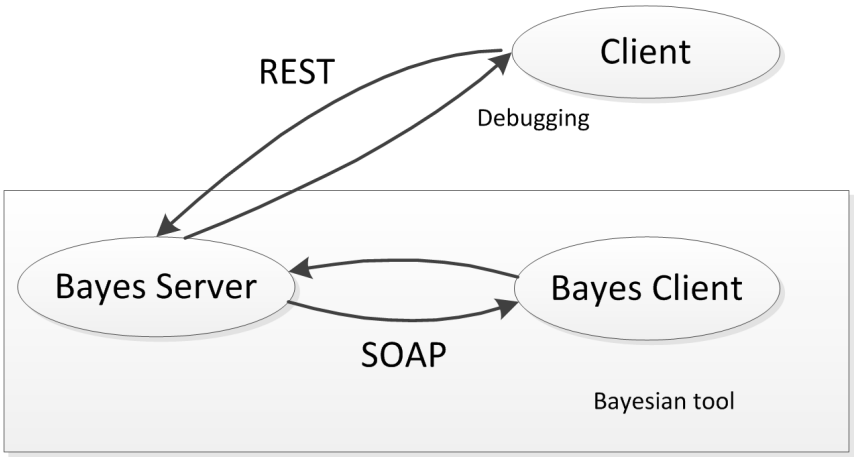


FIGURE 3.1: Bayesian tool system architecture

Bayesian tool consists of Bayes Server and Bayes Client which communicate with each other using SOAP protocol. One can debug current server state using REST as depicted in Figure 3.1.

All the computations are done on the server side, leaving only viewing and control to the Bayes Client. This architecture is a perfect example of *model-view-controller* where:

- *model* - manages data and application behaviour, responds to control commands and requests for information about its state from the *view*
- *view* - renders model into a suitable form for GUI presentation
- *controller* - receives user input and initiates interaction by making calls to *model*

In this case *BS* is model as it computes all the probabilities, stores graphs and responds to user calls. *BC* is view and controller as it displays Bayesian networks with probability distributions and makes calls to *BS* when executing tests.

Thanks to *model-view-controller* architecture it is easy to change *BC* to any client which communicates over REST or SOAP.

3.1.2 Service specification

Bayes server implements two communication protocols - REST and SOAP. REST runs on port **8080** by default and SOAP is served on **8081** by default. These protocols run simultaneously. One can issue some commands on SOAP and some on REST, as described in section 3.6.2, especially

when REST is used for Debug. All the REST commands are implemented as GET commands even though some of them change state. This enables the use of a Web browser as a debugging tool. Some methods have obligatory parameters which are given in sections 3.1.3 and 3.1.4. There are some security policy issues that need to be met. These are imposed by *Microsoft* and described in section 3.1.5.

3.1.3 REST methods

Request	Body	Return value	Description
127.0.0.1:8080/BayesServer/GetGraphList	-	XML from 3.3.1	Returns the list of available graphs.
127.0.0.1:8080/BayesServer/GetGraph/ graphNumber={int}	-	XML from 3.3.2	Downloads a complete graph (structure and CPTs).
127.0.0.1:8080/BayesServer/AccomplishTest/ graphNumber={int}&testNumber={int}& working={bool}	-	XML from 3.3.5	Accomplishes chosen test and fires up inference.
127.0.0.1:8080/BayesServer/ GetRankingOfMostProbableFaults/ graphNumber={int}	-	XML from 3.3.3	Gets the ranking of most probable faults that is the ranking of parts which are broken with the highest probability.
127.0.0.1:8080/BayesServer/ResetCalculations	-	XML from 3.3.5	Resets calculations.
127.0.0.1:8080/BayesServer/GetBestVOITests/ graphNumber={int}	-	XML from 3.3.4	Gets the ranking of tests which provide most inference information.

TABLE 3.1: REST interface

Warning: Use *ResetCalculations* with caution. This method will cause graph reload on the server side and will delete all your inference progress resulting in loss of possibly valuable data. This method does NOT affect all clients.

3.1.4 SOAP methods

Request	Body	Return value	Description
http://127.0.0.1:8081/?wsdl	-	XML	Returns WSDL definition of BayesServerService.
http://127.0.0.1:8081/clientaccesspolicy.xml	-	XML from 3.1.5	Returns an XML required by Silverlight security policy.
http://127.0.0.1:8081/crossdomain.xml	-	XML from 3.1.5	Returns an XML required by Silverlight security policy.
GetGraphList();	-	XML from 3.3.1	Returns the list of available graphs.
GetGraph(int graphNumber);	-	XML from 3.3.2	Downloads a complete graph (structure & CPTs).
AccomplishTest(int graphNumber, int testNumber, bool working);	-	XML from 3.3.5	Accomplishes chosen test and fires up inference.
GetRankingOfMostProbableFaults(int graphNumber);	-	XML from 3.3.3	Gets the ranking of most probable faults that is the ranking of parts which are broken with the highest probability.
ResetCalculations();	-	XML from 3.3.5	Resets calculations.
GetBestVOITests(int graphNumber)	-	XML from 3.3.4	Gets the ranking of tests which provide most inference information.

TABLE 3.2: SOAP interface

Warning: Use *ResetCalculations()* with caution. This method will cause graph reload on the server side and will delete all your inference progress resulting in loss of possibly valuable data. This method does NOT affect all clients.

3.1.5 Policy access XMLs

Clientaccesspolicy.xml and *crossdomain.xml* are files described in paper [13]. They guard SOAP communication against many types of security vulnerabilities, *cross-site forgery* as one of them. Malicious *Silverlight* control, such as transmitting unauthorized commands to a third-party service calls are possible if crossdomain policy is not controlled. Following this policy the service must explicitly opt-in to allow cross-domain access. In order to do that one has to place a *clientaccesspolicy.xml* and *crossdomain.xml* files at the root of the domain where the service is hosted. To download policy XMLs served by BayesServer use SOAP methods described in 3.1.4.

Clientaccesspolicy.xml

```
1 <?xml version="1.0" encoding="utf-8" ?>
2 <access-policy>
3     <cross-domain-access>
4         <policy>
5             <allow-from http-request-headers="*">
6                 <domain uri="*"/>
7             </allow-from>
8             <grant-to>
```

```
9                 <resource include-subpaths="true" path="/"/>
10            </grant-to>
11        </policy>
12    </cross-domain-access>
13 </access-policy>
```

Crossdomain.xml

```
1  <?xml version="1.0"?>
2  <!DOCTYPE cross-domain-policy SYSTEM
3      "http://www.macromedia.com/xml/dtds/cross-domain-policy.dtd">
4  <cross-domain-policy>
5      <allow-http-request-headers-from domain="*" headers="*"/>
6  </cross-domain-policy>
```

3.1.6 Using REST and SOAP for inference in Bayes Server

To do inference in Bayesian networks using Bayes Server one has to obey strict sequence of method calls:

1. GetGraphList - gets graph list along with their unique ids;
   One has to get the list of graphs, pick one graph and save its id.

2. GetGraph - downloads a specific graph;
   One has to download a specific graph giving its id. Graph XML contains structure, CPTs and all needed probabilities.

3. GetBestVOITests [OPTIONAL] - downloads tests which are recommended to execute in the first place.
   VOI tests are described in section 3.6.5.

4. GetRankingOfMostProbableFaults [OPTIONAL] - gets the list of most probable faults that is parts that are broken with the highest probability.
   One can display the list of most probable faults in GUI and let user know which parts are most probably broken throughout reasoning. *MPF* rankings are described in section 3.6.5.

5. AccomplishTest - executes a specific tests
   One has to give a boolean result of the test. It can be positive which means the part is working or negative which means that something is broken.

6. GOTO 3.

By executing following tests one adds new facts to the Bayesian network. Depending on the probability composition which should enable convergence and the integrity of new facts, one should end up with single part having considerably greater $P(\neg X)$ than the rest of the nodes. This part is most probably broken and is the result of the diagnostic process. Bayesian inference is described in detail in section 2.7.

3.2 Algorithms used

Inference in Bayesian networks has an exponential complexity dependant on the network's treewidth. Bayes Server limits the updates of nodes to the ones that have a direct path to the executed test. This is equivalent to the update of the entire network based on the notion that:
$P(A,B)+P(A,\neg B)=P(A)$.

3.2.1 Bayesian inference algorithm

The process of recalculating probabilities starts when the *accomplishTest* REST/SOAP call occurs.

```
1  public void accomplishTest(int testNmbr, bool working)
2  {
3      //propagate probability from leaf–nodes
4      propagateCurrentState();
5
6      //get the prior probability of the test that has been executed (e.g. P(B))
7      double p = getProb(testNmbr, working);
8      double d;
9
10     //get leaves that are dependant on the executed test (e.g. {R,C})
11     //these probabilities are needed to update posterior probability
12     List<int> parts = getSubLeaves(testNmbr);
13     List<double> probs = new List<double>();
14     for (int i = 0; i < parts.Count; i++)
15     {
16         //get the intersection probability e.g. P(B|R)*P(R)
17         d = getIntersectionProb(testNmbr, parts[i], working, true);
18         probs.Add(d / p);
19     }
20
21     //update posterior probabilities – i.e. posterior P(C) = P(C|B)
22     //and posterior P(R) = P(R|B)
23     for (int i = 0; i < probs.Count; i++)
24     {
25         nodes[parts[i]].normal_working_Probability = probs[i];
26         nodes[parts[i]].abnormal_broken_Probability = 1 – probs[i];
27     }
28
29     propagateCurrentState();
30 }
```

Note: The above listing is just a C#-like pseudo-code. Full listing of this algorithm's code along with extensive comments is available in chapter 3.9. All comments and explanatory examples are based on Bayesian network in figure 2.11 and computations in section 2.7.2.

Node number of the executed test is passed as input to the *accomplishTest()* method along with the test's outcome which can either be positive or negative.

In the 4^{th} line *propagateCurrentState()* propagates the probability from leaf-nodes to tests by simply calculating P(X) of every ancestor of the current node. This is done by the recursion

call of *propagateSubtree()* method which goes down to all dependant leaves and propagates the probability all the way to the test-nodes.

The *propagateSubtree()* method has no effect on leaves as they have no parents and no probability to update. Other nodes are updated according to their *CPTs*. Following the example in figure 2.11 nodes R and C stay with their probabilities intact. The probability P(Hr), on the other hand, is calculated according to: $P(Hr) = P(Hr|R,C) * P(R) * P(C) + P(Hr|R,\neg C) * P(R) * P(\neg C) + P(Hr|\neg R,C) * P(\neg R) * P(C) + P(Hr|\neg R,\neg C) * P(\neg R) * P(\neg C)$.

In the 7^{th} line *getProb()* gets probability P(X) of the test which has been executed. According to the example from figure 2.11 this is P(B) = 0.107545. The *getProb()* method is discussed later in the section.

Leaves that are dependant on the executed test are a result of *getSubLeaves()* method in 12^{th} line. These are leaf-nodes that have a direct path to the performed test and so are affected by its execution. In figure 2.11 these are {R,C}.

In 17^{th} line *getIntersectionProb()* is executed which gets the intersection probability, that is the probability $P(testNode|dependantLeaf) * P(dependantLeaf)$. Following the example in figure 2.11 that would be: $P(B|R) * P(R)$. This method operates with the help of recursion in the following manner: $P(B|R) * P(R) = [P(B|Hr) * P(Hr|R) + P(B|\neg Hr) * P(\neg Hr|R)] * P(R) = P(B|Hr) * P(Hr|R) * P(R) + P(B|\neg Hr) * P(\neg Hr|R) * P(R)$, where $P(Hr|R) * P(R)$ and $P(\neg Hr|R) * P(R)$ are passed on recursively as *getIntersectionProb(Hr, R, true, partWorking)*; and *getIntersectionProb(Hr, R, true, partWorking)*;

In line 25^{th} and 26^{th} posterior probabilities are updated. This is done for all dependant leaves that are calculated with the help of *getSubLeaves*(). According to the Bayesian network in figure2.11 the update for leaf R is: *posterior* $P(R) = P(R|B) = 0.257862476$.

The whole inference ends with probability propagation from leaf-nodes. Thanks to the latter process one can see the probability change in Bayes client as BC just reads $P(X)$ probabilities and displays them.

3.2.2 Sampling algorithm

Sampling algorithms are implemented using *SMILE* library. The Bayes server's *BayesianLib.cs* contains the complete implementation of *SMILE's* lib usage. The *onUpdateTestEvent()* is fired after each test execution from *Graph.accomplishTest(int testNmbr, bool working)*;

```
1  static public void onUpdateTestEvent(Graph graph,int testNmbr, bool working)
2  {
3      //get node's name
4      string executedTestName = graph.getNodeNameBasedOnNodeId(testNmbr);
5      //convert bool working to SMILE's 'T', 'F' notation
6      string updateStatus = working ? "T" : "F";
7
8      //select appropriate sampling algorithm – combo box in Bayes server's GUI
9      graph.bayesianNet.BayesianAlgorithm = chooseSamplingAlgBasedOnComboInBS();
10
11     //update beliefs and set new evidence
12     graph.bayesianNet.UpdateBeliefs();
```

```
13      graph.bayesianNet.SetEvidence(executedTestName, updateStatus);
14      graph.bayesianNet.UpdateBeliefs();
15
16      foreach (var node in graph.nodes)
17      {
18          try
19          {
20              if (node.isEmpty == false)
21              {
22                  if (node.nodeName == "" || node.nodeName == null)
23                  {
24                      Console.WriteLine("Error: Node with empty name");
25                      continue;
26                  }
27                      String[] outcomeIds = graph.bayesianNet.GetOutcomeIds(node.nodeName);
28                      int outcomeIndex;
29                      for (outcomeIndex = 0; outcomeIndex < outcomeIds.Length; outcomeIndex++)
30                          if ("T".Equals(outcomeIds[outcomeIndex]))
31                              break;
32
33                      double[] probValues = graph.bayesianNet.GetNodeValue(node.nodeName);
34                      double true_prob = probValues[outcomeIndex];
35
36                      node.normal_working_Probability = true_prob;
37                      node.abnormal_broken_Probability = 1 - true_prob;
38              }
39          }
40          catch (Exception e)
41          {
42              Console.WriteLine("Bayesian Lib failed at " + executedTestName + ": " + e.ToString());
43          }
44      }
45
46      Console.WriteLine("Probabilities refreshed");
47  }
```

In lines 4-9 one gets the node's name, converts the boolean *working* property to SMILE's *'T'*, *'F'* format and selects appropriate sampling algorithm based on combo box in Bayes server's GUI. From line 12-14 new evidence is set and beliefs are updated (one propagates probabilities). From line 16-44 one updates the graph's $P(X)$ probabilities. More information on SMILE's library usage can be found in section 3.5.1.

3.2.3 Best VOI test selection algorithms

The theory behind best VOI test selection and MPF ranking is described in section 3.6.5. Summarizing: predicting valuable test execution is difficult and crucial for cutting down number of accomplished tests. There is no better way, however, than trying to execute tests and watching results which is computationally hard.

Bayes server implements the following VOI test selection algorithms:

- Simple
- Exhaustive Search (ES)
- Exhaustive Search (ES) based only on execution of broken tests

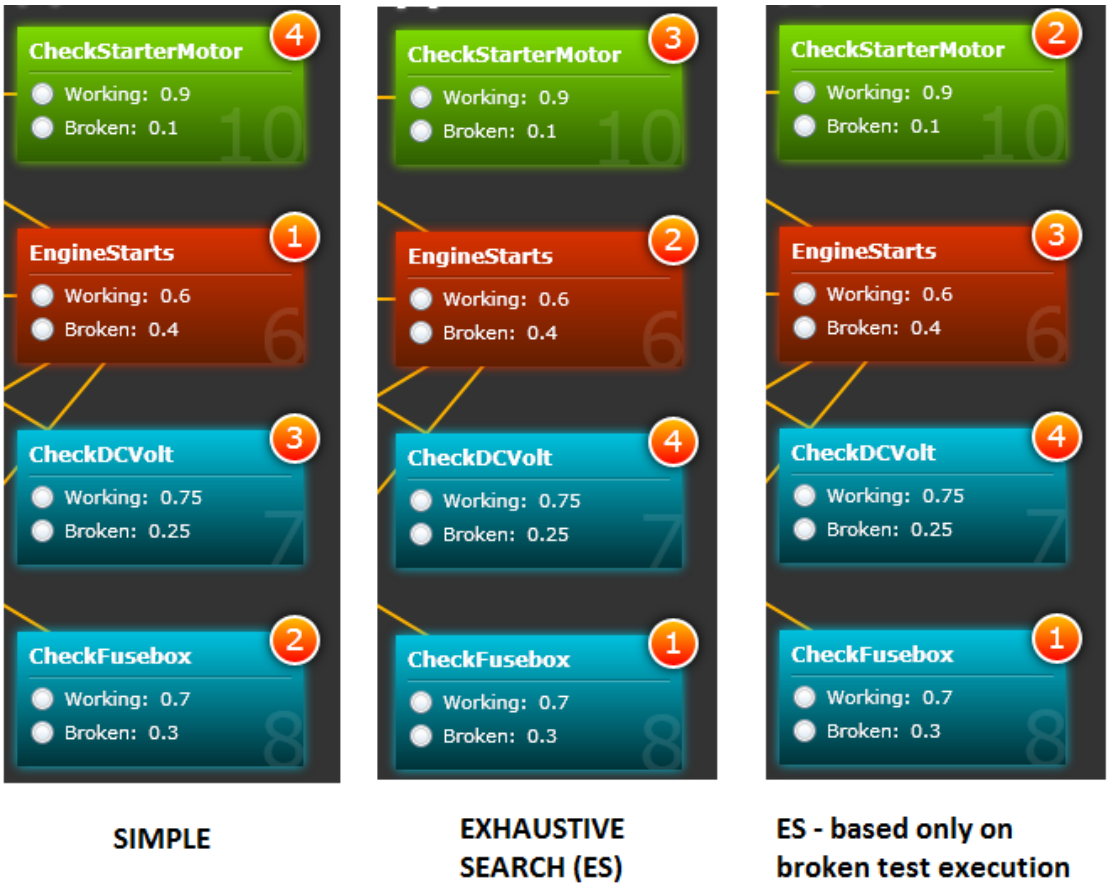


FIGURE 3.2: Recommendations from different best VOI test selection algorithms

Description of algorithms

There are three algorithms used for the construction of VOI test rankings in Bayes server. They differ in computational complexity and accuracy. An ideal algorithm should calculate the lucrativeness of the tests through measuring the *entropy* before and after execution of every test. The difference of entropy is called "*mutual information*" (section 3.6.5). The Exhaustive Search (ES) algorithm follows this definition and resembles the exact algorithm.

1. Simple
   Takes tests which were not executed yet and orders them according to the descending '*broken*' probability. Tests cannot be repeated which results from their definition - providing *broken/working* probability is final in Bayesian reasoning. There is, however, a chance to repeat the tests many times before supplying *broken/working* information if the test is cheap

to make. One needs to take into account that the sole purpose of VOI test ranking algorithms is to minimize the number of executed tests and so speed up the reasoning process. The *Simple* algorithm is based on the notion that the bigger the probability of test failure is, the bigger chance one has of figuring out which part is broken. This is because most parts have less than two tests associated with them and the failure of one of these tests sets part's failure probability $P(\neg X)$ to values near 1.0. This results in an almost sealed diagnosis of such a part. The *Simple* algorithm is least complicated and fast.

2. Exhaustive Search (ES)
   This algorithm follows the exact algorithm's definition. Just as the Simple algorithm it is executed only for tests which were not executed yet. For every such test two Bayesian network clones are made and the test is executed with positive and negative outcome. Next, $P(X)$ probability differences are calculated on all part nodes. Finally these differences are added to create probability difference for positive execution and probability difference for negative execution. These two differences are added which gives *probability gain* for a single test.

3. Exhaustive Search (ES) based only on negative execution of tests
   This algorithm follows the same convention as ES. It is twice faster, though, as it is executed only for the negative outcome of tests. Negative execution was chosen as the primary one as in most scenarios negative execution changes $P(X)$ probabilities a lot more than the positive execution. In other words in *ESn* $P(X)$ probability differences are calculated on all part nodes only after negative execution of the test which then gives *probability gain* for this specific test.

Exhaustive Search (ES) algorithm

Exhaustive Search (*ES*) algorithm was described in enumeration 3.2.3.2. This will be extended with pseudo-code. *ES* is described here in detail as it is most similar to the exact algorithm. Information on source code of the other two algorithms can be found in section 3.9.

```
1  private List<Node> ExhastiveSearchForBestVOITests
2                     (Graph inGraph, List<Node> not_executed_tests, List<Node> parts_to_calc_diff)
3  {
4      List<VOI_InternalRanking> internalRanking = new List<VOI_InternalRanking>();
5      List<Node> outputRanking = new List<Node>();
6      foreach (Node test in not_executed_tests)
7      {//for each test which was not executed yet
8          //clone graphs for positive and negative execution
9          Graph newGraph = (Graph)inGraph.Clone();
10         Graph newGraph2 = (Graph)inGraph.Clone();
11
12         //positive test execution:
13         //get prior probabilities, accomplish test on a cloned graph, get posterior probabilities
14         double[] beforeWorkProbs = newGraph.getWorkingProbsOfSelectedNodes(parts_to_calc_diff);
15         newGraph.accomplishTest(test.nodeIDNumber, true);
16         double[] afterWorkProbs = newGraph.getWorkingProbsOfSelectedNodes(parts_to_calc_diff);
17         //calculate P(X) diff
```

```
18          double diffWorking = newGraph.calculateProbDiffAfterTestExecution
19                                          (beforeWorkProbs, afterWorkProbs);
20          //negative test execution:
21          //get prior probabilities, accomplish test on a cloned graph, get posterior probabilities
22          double[] beforeWorkProbs2 = newGraph2.getWorkingProbsOfSelectedNodes(parts_to_calc_diff);
23          newGraph2.accomplishTest(test.nodeIDNumber, false);
24          double[] afterWorkProbs2 = newGraph2.getWorkingProbsOfSelectedNodes(parts_to_calc_diff);
25          //calculate P(X) diff
26          double diffBroken = newGraph2.calculateProbDiffAfterTestExecution
27                                          (beforeWorkProbs2, afterWorkProbs2);
28
29          //we get the mutual information by adding probabilities
30          //of positive and negative test execution
31          double diff = diffWorking + diffBroken;
32          //store mutual information along with the test
33          internalRanking.Add(new VOI_InternalRanking(test, diff));
34      }
35      //sort according to diff (descending) - the higher diff the better
36      internalRanking.Sort(delegate(VOI_InternalRanking a, VOI_InternalRanking b)
37          {
38              int xdiff = (int)((a.prob_diff - b.prob_diff) * 10000);
39              if (xdiff != 0) return xdiff;
40              return (int)((a.prob_diff - b.prob_diff) * 10000);
41          });
42      internalRanking.Reverse();
43      //clone to -> List<Node>
44      foreach (var intRank in internalRanking)
45      {
46          outputRanking.Add(intRank.node);
47      }
48      return outputRanking;
49  }
```

In lines 9-10 the graph is cloned for positive and negative execution of every test which was not executed yet. From line 14 to 16 prior probabilities P(X) are stored. Then a test is accomplished on the cloned graph and posterior probabilities are calculated. The P(X) difference is calculated in line 18 by subtracting posterior and prior P(X) probabilities for each part-node (which were taken from function *parts_to_calc_diff*). In lines 21-25 the same steps are accomplished for the negative test execution. The mutual information is calculated in line 31 by adding probabilities of positive and negative test execution. One creates an internal ranking with mutual information added in line 33. From 36 to 47 the ranking is sorted according to the descending mutual information value. The higher the probability difference, the better. In the end one creates a <Node> list in that order and returns it.

3.3 Communication languages

The main purpose of XMLs described in this section is to allow SOAP communication between Bayes server and Bayes client. They are a direct result of object-xml mapping from Microsoft's .NET *System.Xml* library. Each format will be shortly described. One should place emphasis on the *Graph* communication xml as it serves not only as means of communication but also as an import format to Bayes server.

3.3.1 Graph list - communication XML

Graph list is downloaded as the first step in the communication process. The list contains graphs in `<GraphListElem>` elements. Each of them having `<description>` and `<graphNumber>`. The description can be displayed to the user (as in the combo box in Bayes Client) and the graph's id has to be stored to enable further communication.

```
<?xml version="1.0" encoding="UTF-8"?>
<GraphList>
    <graphList>
        <GraphListElem>
            <!-- graph name -->
            <description>Car failures example</description>
            <!-- graph id -->
            <graphNumber>0</graphNumber>
        </GraphListElem>
        <GraphListElem>
            <description>New Network</description>
            <graphNumber>1</graphNumber>
        </GraphListElem>
    </graphList>
</GraphList>
```

3.3.2 Graph - communication XML

This is the main XML type containing graph nodes and arcs as well as probabilities of leaf-nodes and *CPTs*. Exemplary graph XML describes a Bayesian network from figure 3.8. The example contains just a few nodes, however, as the whole XML is too long.

The GRAPH XML contains two main parts. These are `<nodes>` and `<edgeList>`. The `<Node>` node contains all the information connected with a single node. These are:

- `<nodeName>` - node's name
- `<nodeIDNumber>` - node's id
- `<isEmpty>` - this should always be false for a real node. There is a possibility to hide part of the graph to see the effect of such an operation on the entire structure. When importing a graph without some nodes one can set these nodes' *isEmpty* property to true and delete these nodes' ids from edgeList. Hiding the node means "*deleting*" it from all calculations and inference. This node is also not visible in Bayes Client.

- <abnormal_broken_Probability> - this node denotes $P(\neg X)$
- <normal_working_Probability> - this node denotes $P(X)$
- <hasAncestors> - this is a *boolean* property set to true if the node has any ancestors.
- <hasDescendants> - this is a *boolean* property set to true if the node has any descendants.
- <isTest> - this is a *boolean* property set to true if the node is a test which means that it can be executed with the method *executeTest()*. Additional information in section 3.1.4.
- <condProbTable_CPT> - this node will be describe in the end.

The second part is an edge list which contains:

- <isEmpty> - this is a *boolean* property telling whether the node has any descendants
- <originNode> - this is equal to node's id
- <descendants> - this node contains a list of descendants wrapped in <int></int>

The conditional probability table of each node contains:

- <ancestorsSequence> - this is a list of ancestors wrapped in <int></int>
- <originNode> - this is equal to node's id
- list of <CondProbAnc> where each contains:
  - <brokenValue> - this is the $P(\neg H|\neg X)$ probability (on condition that this is the conditionalProbAnc[0] element and has a single parent). The brokenValue of conditionalProbAnc[0] with single parent is $P(\neg H|X)$ probability.
  - <workingValue> - this is the $P(H|\neg X)$ probability (on condition that this is the conditionalProbAnc[0] element and has a single parent). The brokenValue of conditionalProbAnc[0] with single parent is $P(H|X)$ probability.
  - <CPTRowArgValuesStr> - contains the parent's value string. This is passed on in order for Bayes Client to know what format of boolean values one uses. There is a possibility to use strings as well as digits. The standard representation is binary.

Conditional probability tables in Graph XML

Values inside <CondProbAnc> node are $P(\neg H|X)$ and $P(H|X)$ probabilities. Elements in <CPTRowArgValuesStr> should create a binary sequence, so for 2 parents one would have: *{0;0;}, {0;1;},{1;0;},{1;1;}*. These values represent parents' boolean states.

In the example below the node has one parent and the relation is $X \rightarrow Y$:

```
1 <CondProbAnc>
2     <brokenValue>0.44923248894881296</brokenValue>
3     <workingValue>0.550767511051187</workingValue>
4 <CPTRowArgValuesStr>0;</CPTRowArgValuesStr>
```

```
</CondProbAnc>
<CondProbAnc>
    <brokenValue>0.737545512413055</brokenValue>
    <workingValue>0.262454487586945</workingValue>
    <CPTRowArgValuesStr>1;</CPTRowArgValuesStr>
</CondProbAnc>
```

These values denote the probabilities:

X	$P(Y\|X)$	$P(\neg Y\|X)$
0	0.551	0.449
1	0.262	0.738

TABLE 3.3: CPT example

Graph example XML

```
<?xml version="1.0" encoding="UTF-8"?>
<Graph xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance"
       xmlns:xsd="http://www.w3.org/2001/XMLSchema">
  <graphName>New Network</graphName>
  <nodes>
    <Node>
      <!-- node name -->
      <nodeName>CheckStarterMotor</nodeName>
      <!-- node id number -->
      <nodeIDNumber>4</nodeIDNumber>
      <!-- whether the node is hidden -->
      <isEmpty>false</isEmpty>
      <!-- P(~X) -->
      <abnormal_broken_Probability>0.5</abnormal_broken_Probability>
      <!-- P(X) -->
      <normal_working_Probability>0.5</normal_working_Probability>
      <!-- boolean; whether the node has any ancestors -->
      <hasAncestors>true</hasAncestors>
      <!-- boolean; whether the node has any descendants -->
      <hasDescendants>false</hasDescendants>
      <!-- boolean; whether the node is a test (can be executed) -->
      <isTest xsi:nil="true" />
      <condProbTable_CPT>
        <!-- ancestors in the form of: <int>0</int><int>1</int> etc. -->
        <ancestorsSequence>
          <int>0</int>
        </ancestorsSequence>
        <!-- CPT sequence -->
        <conditionalProbAnc>
          <CondProbAnc>
            <!-- P(~CSM|SM) given SM=0 -->
            <brokenValue>0.44923248894881296</brokenValue>
```

```
33              <!-- P(CSM|SM)  given SM=0 -->
34              <workingValue>0.550767511051187</workingValue>
35              <CPTRowArgValuesStr>0;</CPTRowArgValuesStr>
36            </CondProbAnc>
37            <CondProbAnc>
38              <!-- P(~CSM|SM) given SM=1 -->
39              <brokenValue>0.737545512413055</brokenValue>
40              <!-- P(CSM|SM)  given SM=1 -->
41              <workingValue>0.262454487586945</workingValue>
42              <CPTRowArgValuesStr>1;</CPTRowArgValuesStr>
43            </CondProbAnc>
44          </conditionalProbAnc>
45        </condProbTable_CPT>
46      </Node>
47    </nodes>
48    <edgeList>
49      <NeighbourListElem>
50        <!-- boolean property telling whether the node has any descendants -->
51        <isEmpty>false</isEmpty>
52        <!-- originNode -> child -->
53        <originNode>0</originNode>
54        <!-- list of children in the form of: <int>0</int><int>1</int> etc. -->
55        <descendants>
56          <int>5</int>
57          <int>4</int>
58        </descendants>
59        <ancestors />
60      </NeighbourListElem>
61    </edgeList>
62    <mainFault xsi:nil="true" />
63    <listOfPerformedTests />
64  </Graph>
```

3.3.3 Fault ranking - communication XML

Fault ranking XML is a means of transporting the list of *MPF* rankings described in section 3.6.5. Each `<Fault>` element contains `<FaultName>` and `<FaultProbability>`. Fault name is equivalent to node's name and should be displayed to the user along with probability. The list is a ready ranking staring from the most probable fault.

```
1  <?xml version="1.0" encoding="UTF-8"?>
2  <FaultRanking>
3      <faultList>
4          <Fault>
5              <!-- fault name -->
6              <FaultName>Battery</FaultName>
7              <!-- fault probability taken from P(~X) -->
8              <FaultProbability>0.35</FaultProbability>
9          </Fault>
```

```
        <Fault>
            <FaultName>FuseBox</FaultName>
            <FaultProbability>0.3</FaultProbability>
        </Fault>
    </faultList>
</FaultRanking>
```

3.3.4 Best VOI test ranking - communication XML

VOI test ranking XML transports the list of best VOI tests described in section 3.6.5. Each `<VOITest>` element contains `<nodeID>`, `<probabilityGain>` and `<testName>`. Test name is equivalent to node's name and should be displayed to the user along with probability. The node id of the chosen test should be stored and sent to *executeTest()* method. The list is a ready ranking starting from best tests.

```
<?xml version="1.0" encoding="UTF-8"?>
<VOITestRanking>
    <testRanking>
        <VOITest>
            <!-- node id -->
            <nodeID>6</nodeID>
            <!-- supposed (alleged) probability gain from executing test no. 6 -->
            <probabilityGain>0.9</probabilityGain>
            <!-- name of the test -->
            <testName>t1</testName>
        </VOITest>
        <VOITest>
            <nodeID>7</nodeID>
            <probabilityGain>0.7</probabilityGain>
            <testName>t2</testName>
        </VOITest>
        <VOITest>
            <nodeID>8</nodeID>
            <probabilityGain>0.6</probabilityGain>
            <testName>t3</testName>
        </VOITest>
    </testRanking>
</VOITestRanking>
```

3.3.5 Operation status - communication XML

The operation status XML is returned from the *AccomplishTest* and *ResetCalculations* methods. This is just a *boolean* response contained in `<result>` tag.

```
<?xml version="1.0" encoding="UTF-8"?>
<SoapRestEventResponse>
    <!-- boolean response -->
    <result>SUCCEEDED</result>
</SoapRestEventResponse>
```

3.3.6 BIF format version 0.3

BIF stands for *Bayesian Interchange Format* (*Interchange Format for Bayesian Networks*). It is described thoroughly in paper [14]. This format was initially created in 1998 and is also called XMLBIF. It is mostly known thanks to its implementation in WEKA [15]. Inside the interchange file one has the main node `<BIF>`. `<NETWORK>` node is defined inside *BIF* by stating its `<NAME>` and node definitions with `<VARIABLE>`. The `<VARIABLE>` node apart from its `<NAME>` has also a few `<OUTCOME>` nodes. These define possible values and are most commonly set to '*0*' and '*1*'. There can be more of them however (the minimum number is of course 2 which is derived from the definition of Bayesian network). One can define conditional probability tables with node `<DEFINITION>`. Actually there are two types of `<DEFINITION>` nodes:

- `<DEFINITION>` node with `<GIVEN>` value - represent conditional probabilities P(*for*|*given*)
- `<DEFINITION>` node without `<GIVEN>` value - represent probabilities P(*for*)

BIF conditional probability tables

BIF *CPTs* are injected inside the `<TABLE>` node. They are very similar to the native format of Bayes Server described in section 3.3.2. There is no requirement to put newline characters at the end of every CPT row so these two tables are equal:

0.90 0.10 \r\n
0.01 0.99 \r\n

equals

0.90 0.10 0.01 0.99 \r\n

TABLE 3.4: BIF CPT example

WEKA's implementations is coherent and *always* puts newline characters in *every row* of the CPT (left-table's version from 3.4).

Values in `<TABLE>` should create a binary sequence just as in native format of Bayes Server (3.3.2), so for 2 parents one would have: {0;0;}, {0;1;},{1;0;},{1;1;}. These values represent parents' boolean states. This means that the table 3.4 transforms into:

X	$P(Y\|X)$	$P(\neg Y\|X)$
0	0.10	0.90
1	0.99	0.01

TABLE 3.5: CPT example

BIF example

```
1 <?xml version="1.0" encoding="UTF-8"?>
2 <?xml version="1.0"?>
3 <BIF VERSION="0.3">
4   <NETWORK>
5     <!-- network name -->
6     <NAME>New Network</NAME>
7     <!-- single node definition -->
```

```
8       <VARIABLE TYPE="nature">
9         <NAME>StarterMotor</NAME>
10        <OUTCOME>Value1</OUTCOME>
11        <OUTCOME>Value2</OUTCOME>
12        <PROPERTY>position = (47,67)</PROPERTY>
13      </VARIABLE>
14      <VARIABLE TYPE="nature">
15        <NAME>CheckStarterMotor</NAME>
16        <OUTCOME>Value1</OUTCOME>
17        <OUTCOME>Value2</OUTCOME>
18        <PROPERTY>position = (53,147)</PROPERTY>
19      </VARIABLE>
20      <VARIABLE TYPE="nature"></VARIABLE>
21      <!-- Probability distributions -->
22      <DEFINITION>
23          <!-- probabilities P(StarterMotor) -->
24          <FOR>StarterMotor</FOR>
25          <TABLE> 0.02 0.98  </TABLE>
26      </DEFINITION>
27      <DEFINITION>
28          <FOR>CheckStarterMotor</FOR>
29          <GIVEN>StarterMotor</GIVEN>
30          <!-- probabilities P(CheckStarterMotor|StarterMotor) -->
31          <TABLE> 0.90 0.10 0.01 0.99 </TABLE>
32      </DEFINITION>
33    </NETWORK>
34  </BIF>
```

BIF import

Overall description Bayes Server can easily import *BIF* files from its GUI which is described in section 3.6.4. There is an option called "*convert BIF to GRAPH*" which takes a *.BIF file and saves *.GRAPH in the designated path. One should save converted graphs to ./Graphs directory where they will be automatically loaded by the server. By clicking "*Refresh*" button one forces graph reload so the converted graph will be available for reasoning. Example BIF file can be created with the help of WEKA software [15]. WEKA's internal "*Bayes net editor*" available from tools is able to load, visualise and save Bayesian networks in *BIF* format.

Value	imported/ignored
network name	IMPORTED
names of nodes	IMPORTED
CTPs	IMPORTED
ancestors list	IMPORTED
node's X,Y coordinates	IGNORED
variable outcome values	IMPORTED

TABLE 3.6: BIF imported values

Imported values The basic structure of the Bayesian network is imported from BIF format as it is: network's name, names of nodes and *CPTs*. The list of ancestors is imported from <DEFINITION> nodes. Ascendants are computed as a reverse list of ancestors. The GRAPH format has more information than the BIF one so some values are computer or taken as constants. Node's $P(X)$ are worth mentioning. In GRAPH format $P(X)$ values (in nodes with ancestors) denote "*the probability of failure*" and are taken from statistical analysis even before the first pass of the inference. They are displayed right after the Bayesian network is loaded by the Bayes Client. After the first pass they are overwritten by values from *propagation pass* (section 2.7.2). The table below presents the source of nodes' property values in the result GRAPH file:

Value	imported/ignored
normal_working_Probability of nodes with ancestors	0.99
abnormal_broken_Probability of nodes with ancestors	0.01
descendants list	COMPUTED
hasAncestors	COMPUTED
hasDescendants	COMPUTED
node IDs	int sequence generator
isEmpty	false
isTest	COMPUTED
CPTRowArgValuesStr	from <OUTCOME> values
listOfPerformedTests	empty

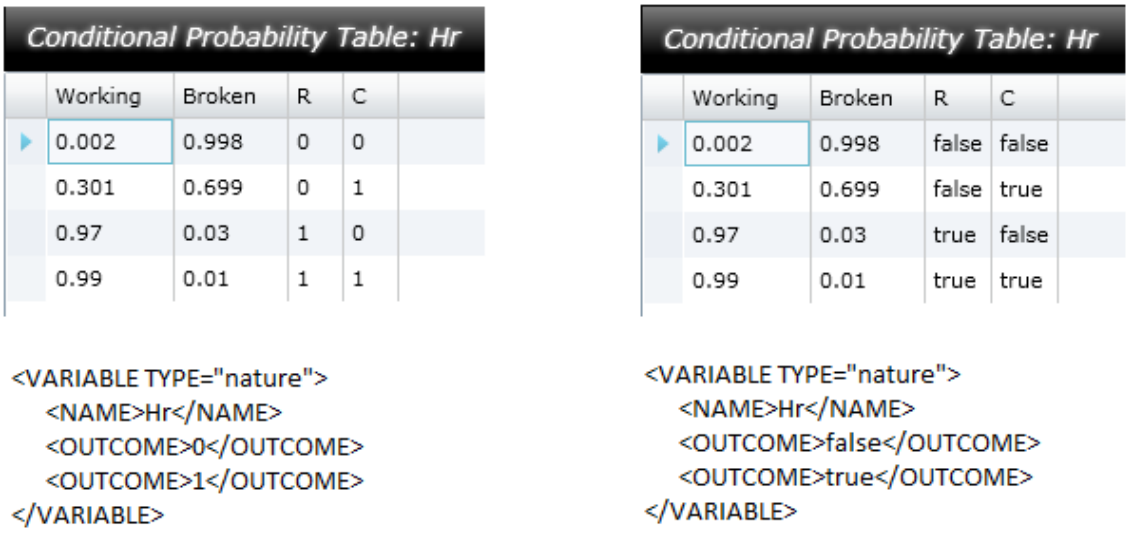
TABLE 3.7: Values origin in the result file

Constants 0.99 and 0.01 are taken as the probability $P(X)$ and $P(\neg X)$ of nodes with ancestors. This is done because there is no information whatsoever on these probabilities in BIF format and a low probability of failure is assumed.

The descendants list and *hasAncestors*, *hasDescendants* properties are easily computed from graph's structure. Nodes are given following integer values starting from 0 as IDs. Nodes with ancestors and no descendant are assumed to be tests. The listOfPerformedTests is always set to null in the import process.

CPTRowArgValuesStr is computed from <OUTCOME> nodes in *BIF* format. One can actually set more than two values as described in section 3.3.6 but the import works only for two values for a node. This is because all logic in Bayes server is limited to binary values of nodes. One can, however, set any string to denote '0' and '1' values. The figure 3.3 shows *CPTs* of node *Hr* with values '*0*', '*1*' and '*false*', '*true*'.

Imported network example As it is clearly visible in the figure 3.4 the only difference between the imported and original Bayesian network is the 0.99 $P(X)$ probability of nodes with ancestors. This probability cannot be imported as described earlier. The imported network behaves exactly the same as the one defined in GRAPH format during the inference process.



Conditional Probability Table: Hr

Working	Broken	R	C
0.002	0.998	0	0
0.301	0.699	0	1
0.97	0.03	1	0
0.99	0.01	1	1

```
<VARIABLE TYPE="nature">
   <NAME>Hr</NAME>
   <OUTCOME>0</OUTCOME>
   <OUTCOME>1</OUTCOME>
</VARIABLE>
```

Conditional Probability Table: Hr

Working	Broken	R	C
0.002	0.998	false	false
0.301	0.699	false	true
0.97	0.03	true	false
0.99	0.01	true	true

```
<VARIABLE TYPE="nature">
   <NAME>Hr</NAME>
   <OUTCOME>false</OUTCOME>
   <OUTCOME>true</OUTCOME>
</VARIABLE>
```

FIGURE 3.3: Different values in BIF's <GIVEN> nodes before the import

3.4 Bayesian networks and CPTs graphical representation

Bayesian network structure is discussed in section 1.2. *BN* Client represents Directed Acyclic Graphs as colored boxes and arcs as lines. Conditional Probability tables are represented as depicted in figure 3.5. *Working*/*Broken* probabilities inside boxes are $P(X)$ and $P(\neg X)$. Following the example in the figure 3.5 one has P(FuseBox) = 0.7 and P(CheckFusebox)=0.7.

Boxes' color depend on P(X) probability value:

- green boxes - high P(X)
- blue boxes - average P(X)
- red boxes - low P(X)

Consequently failed tests/parts are red. Green nodes on the other hand represent working parts and passed tests. A particular node is green if its probability $P(X)$ is larger than 0.75. The node is blue if its probability $P(X) \in (0.4, 0.75]$ and red if $P(X) \leq 0.4$. These values are set in Bayes client: *NetworkGraphNode.xaml.cs*, *UpdateCompleted()*.

In GUI all parts are on the left and all tests are on the right side.

This order is imposed only by the Bayes Client. One can write one's own client and do inference using SOAP/REST methods with any graphical representation.

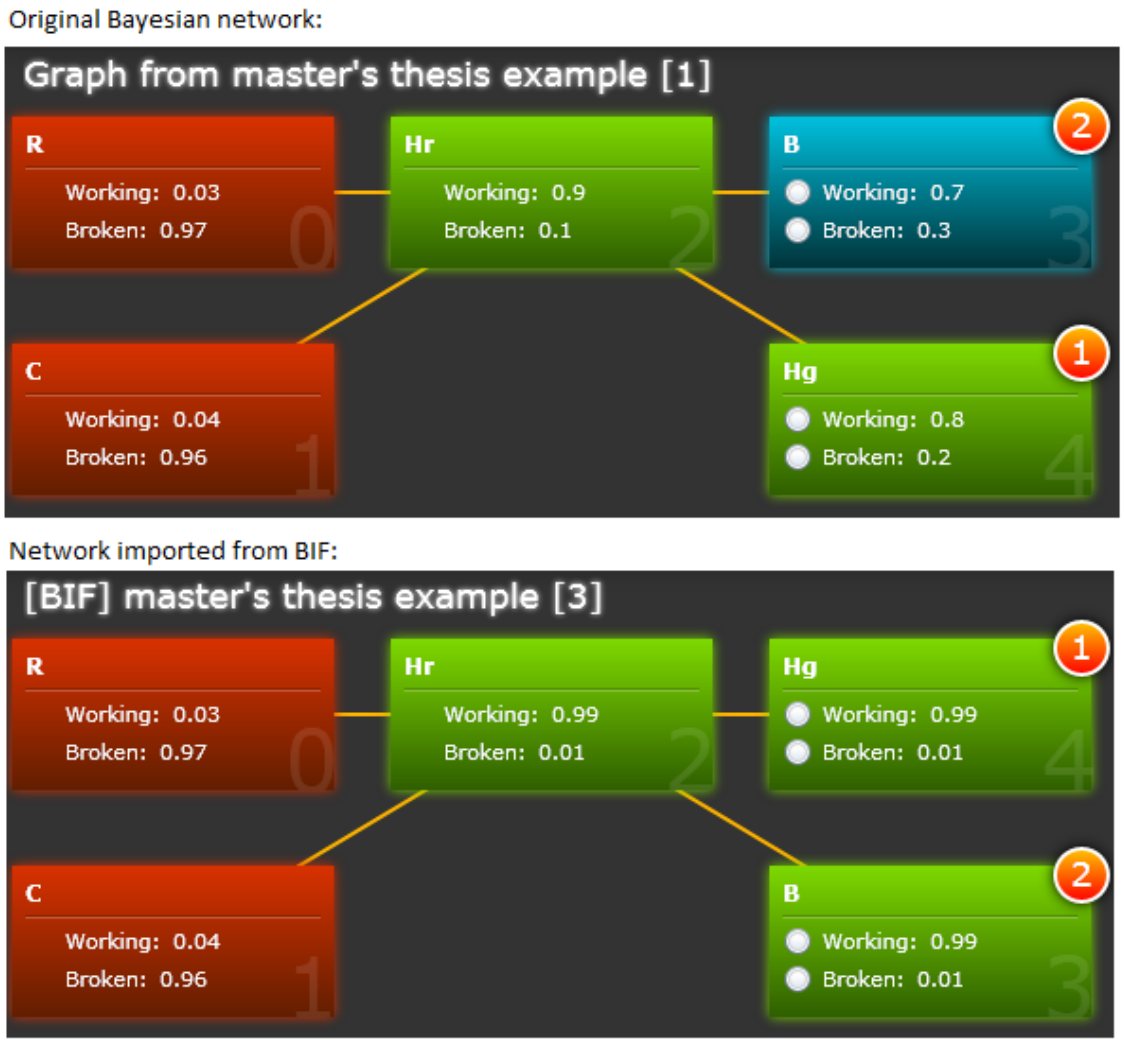


FIGURE 3.4: Original and imported Bayesian network

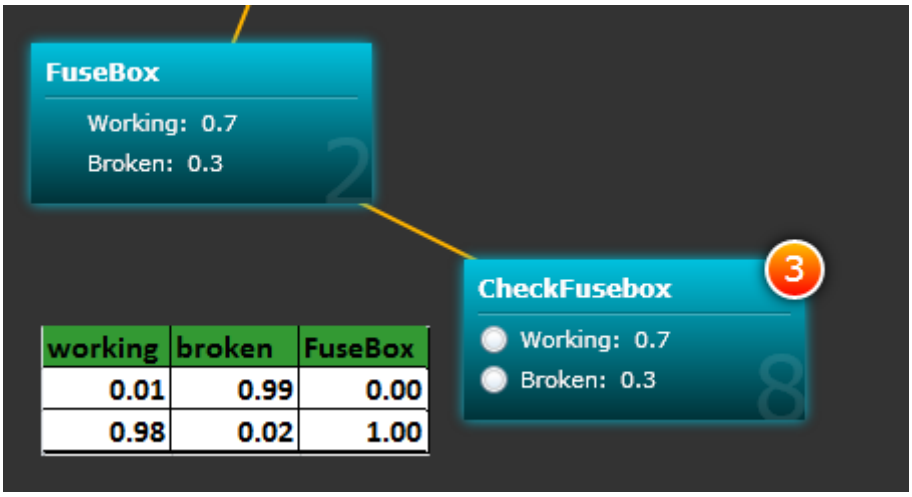


FIGURE 3.5: CPT representation

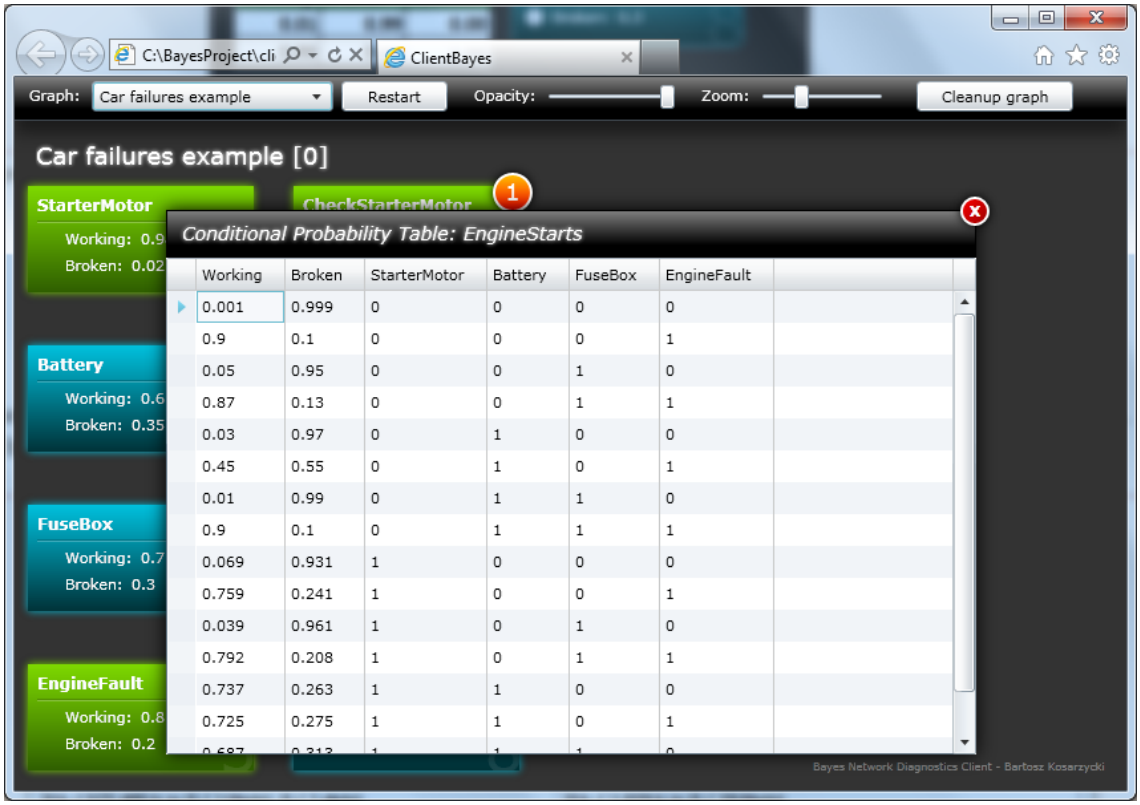
Analysing figure 3.5 one can learn the following information about the graph:

CFB = CheckFusebox; FB = FuseBox;

- P(FB) = 0.7 and P(CFB)=0.7
- P(CFB|FB)=0.98; P(¬CFB|FB)=0.02;
- P(CFB|¬FB)=0.01; P(¬CFB|¬FB)=0.99;

Conditional probability tables are sent from Bayes server using *Graph* XML. More information on this format is described in section 3.3.2.

The conditional probability table of a node can be displayed after **right-clicking** a node as described in section 3.6.



Working	Broken	StarterMotor	Battery	FuseBox	EngineFault
0.001	0.999	0	0	0	0
0.9	0.1	0	0	0	1
0.05	0.95	0	0	1	0
0.87	0.13	0	0	1	1
0.03	0.97	0	1	0	0
0.45	0.55	0	1	0	1
0.01	0.99	0	1	1	0
0.9	0.1	0	1	1	1
0.069	0.931	1	0	0	0
0.759	0.241	1	0	0	1
0.039	0.961	1	0	1	0
0.792	0.208	1	0	1	1
0.737	0.263	1	1	0	0
0.725	0.275	1	1	0	1

FIGURE 3.6: Conditional probability tables in Bayes Client GUI

3.5 Technologies used

The whole Bayesian tool project was written using Visual Studio 2010. Visual Studio project files are not backwards compatible unless one creates a new project, imports source files and adds required references manually. To successfully compile Bayes Server one needs to have *.NET 4.0 Extended* installed (around 52 MB). Bayes Client requires Silverlight as well: *Microsoft Silverlight* (around 145 MB), *Microsoft Silverlight 4.0 SDK* (around 32 MB).

Binaries require *.NET 4.0* and *Microsoft Silverlight.*

3.5.1 Bayes server technologies

Bayes server was written in C# using .NET 4.0 framework. The Server is supposed to run in background hosting SOAP and REST services at the same time. Service specification will be covered in section 3.1.2. XML serialization and communication between modules are done using standard .NET libraries:

- System.ServiceModel.ServiceHost;
- System.ServiceModel.Channels;
- System.Xml;
- System.Net;

Additional inference algorithms are covered using SMILE library described below.

SMILE library

The SMILE library comes from the University of Pittsburgh, precisely their Decision Systems Laboratory. The library is written in C++ and offers a .NET wrapper called SMILE.NET. More information about the library can be found in [16]. Bayes Server uses version from 10/22/2010 and references the following functions:

- UpdateBeliefs()
- SetEvidence()
- AddNode()
- SetOutcomeId()
- AddArc()
- SetNodeDefinition()

The library enables the usage of the following algorithms in Bayesian inference: AisSampling, BackSampling, EpisSampling, Henrion, HeuristicImportance, Lauritzen, LSampling, SelfImportance. Lauritzen is the default algorithm. Example usage can be found in *BayesianLib.cs* from Bayes Server source files.

Algorithm types Library's internal algorithm descriptions are taken from *SMILE* library's wiki [16].

AisSampling The Adaptive Importance Sampling for Bayesian Networks (AIS-BN) algorithm is described in (Cheng and Druzdzel 2000). This is one of the best sampling algorithm available (as of December 2002), surpassed only recently by the APIS-BN algorithm (Yuan and Druzdzel 2003). In really difficult cases, such as reasoning under very unlikely evidence in very large networks, it will produce two orders of magnitude smaller error in posterior probability distributions than other sampling algorithms. Improvement in speed given a desired precision is even

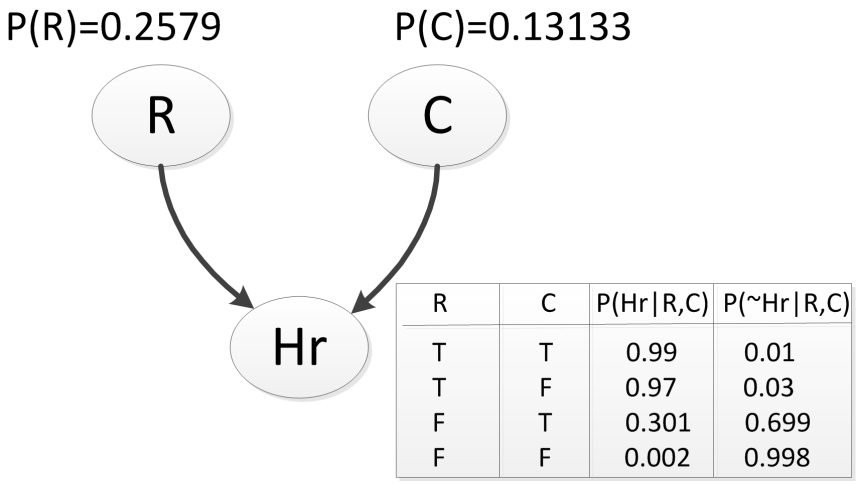
more dramatic. The AIS-BN algorithm is based on importance sampling. According to the theory of importance sampling, the closer the sampling distribution is to the (unknown) posterior distribution, the better the results will be. The AIS-BN algorithm successfully approximate its sampling distribution to the posterior distribution by using two cleverly designed heuristic methods in its first stage, which leads to the big improvement in performance stated above. [16]

EpisSampling The Estimated Posterior Importance Sampling algorithm for Bayesian Networks (EPIS-BN) algorithm is described in (Yuan and Druzdzel 2003). This is quite likely the best sampling algorithm available (as of September 2003). It produces results that are even more precise than those produced by the AIS-BN algorithm and in case of some networks produces results that are an order of magnitude more precise. The EPIS-BN algorithm uses loopy belief propagation to compute an estimate of the posterior probability over all nodes of the network and then uses importance sampling to refine this estimate. In addition to being more precise, it is also faster than the AIS-BN algorithm, as it avoids the costly learning stage of the latter. [16]

Setting conditional probability tables using *SetNodeDefinition* CPTs format of the SMILE library is compatible with the format used by Bayes server. However, one has to remember about putting outcome values in the right order. Bayes server treats 'false' outcome value as primary ones and so node's parents values resemble binary sequence. This sequence is described in GRAPH's CTPs format in section 3.3.2. To make 'false' values primary in SMILE library one has to add the 'false' outcome value first. One has to remember about adding parents in the right order as well.

The order of probabilities is given by considering the state of the first parent of the node as the most significant coordinate (thinking of the coordinates in terms of bits), then the second parent, and so on, and finally considering the coordinate of the node itself as the least significant one.

For the following network part:



R	C	P(Hr|R,C)	P(~Hr|R,C)
T	T	0.99	0.01
T	F	0.97	0.03
F	T	0.301	0.699
F	F	0.002	0.998

FIGURE 3.7: SMILE library CPTs example

One has to add outcome values in the following order:

```
1  net.AddNode(Network.NodeType.Cpt, "R");
```

```
net.SetOutcomeId("R", 0, "F");
net.SetOutcomeId("R", 1, "T");
net.AddNode(Network.NodeType.Cpt, "C");
net.SetOutcomeId("C", 0, "F");
net.SetOutcomeId("C", 1, "T");
net.AddNode(Network.NodeType.Cpt, "Hr");
net.AddArc("R", "Hr");
net.AddArc("C", "Hr");
```

and the CPTs in the following way:

addition order	node itself (Hr)	first parent (R)	second parent (C)	P(Hr|R,C)
1	0	0	0	0.998
2	1	0	0	0.002
3	0	0	1	0.699
4	1	0	1	0.301
5	0	1	0	0.03
6	1	1	0	0.97
7	0	1	1	0.01
8	1	1	1	0.99

TABLE 3.8: SMILE's CPTs addition order

So one has:

```
double[] probabilitiesDef = null;
probabilitiesDef = new double[] { 0.998, 0.002, 0.699, 0.301, 0.03, 0.97, 0.01, 0.99 };
inGraph.bayesianNet.SetNodeDefinition(node.nodeName, probabilitiesDef);
```

Preparing SMILE library for Bayesian inference The *processSingleGraph(Graph inGraph)* function is fired on Bayes server start-up when the list of graphs is loaded. It prepares *SMILE* library for Bayesian inference. Each graph is passed to the function using *inGraph* parameter in a *for loop*.

```
static private void processSingleGraph(Graph inGraph)
{
    try
    {
        if (inGraph.bayesianNet == null && inGraph.edgeList != null)
        {
            if (inGraph.edgeList.Count == 0)
            {
                throw new Exception("inGraph.edgeList.Count == 0");
                return;
            }

            //create new SMILE lib instance
            inGraph.bayesianNet = new Network();
            inGraph.bayesianNet.SampleCount = 5000;

```

```
17              //choose sampling algorithm
18              inGraph.bayesianNet.BayesianAlgorithm = chooseSamplingAlgBasedOnComboInBS();
19
20              //set graph's name
21              inGraph.bayesianNet.Name = inGraph.graphName;
22
23              //add nodes, use node names instead of nodeIDs
24              foreach (var node in inGraph.nodes)
25              {
26                  if (node.isEmpty == false)
27                  {
28                      //add node and set its possible outcome values (like '0','1' or 'true', 'false')
29                      inGraph.bayesianNet.AddNode(Network.NodeType.Cpt, node.nodeName);
30                      inGraph.bayesianNet.SetOutcomeId(node.nodeName, 0, "F");
31                      inGraph.bayesianNet.SetOutcomeId(node.nodeName, 1, "T");
32                  }
33              }
34
35              //add arcs
36              foreach (var edge in inGraph.edgeList)
37              {
38                  if (edge.descendants.Count > 0)
39                  {
40                      if (inGraph.getNodeBasedOnNodeId(edge.originNode).isEmpty == true) continue;
41
42                      foreach (var descendant in edge.descendants)
43                      {
44                          //add arc based on descendants list
45                          inGraph.bayesianNet.AddArc(from,
46                                                     inGraph.getNodeNameBasedOnNodeId(descendant));
47                      }
48                  }
49              }
50
51              //add probabilities
52              foreach (var node in inGraph.nodes)
53              {
54                  if (node.isEmpty == false)
55                  {
56                      if (node.hasAncestors)
57                      {
58                          if (node.condProbTable_CPT != null &&
59                              node.condProbTable_CPT.ancestorsSequence != null &&
60                              node.condProbTable_CPT.ancestorsSequence.Length > 0)
61                          {
62                              //add conditional probability tables
63                              //refer to BayesianLib.cs: processSingleGraph(Graph inGraph)
64                              //CPTs' format is described in section:
```

```
65                              //'Setting conditional probability tables using SetNodeDefinition'
66                          }
67                      }
68                      else
69                      {
70                          //add P(X) and P(~X) probability
71                          probabilitiesDef = new double[2];
72                          probabilitiesDef[0] = node.abnormal_broken_Probability; //F
73                          probabilitiesDef[1] = node.normal_working_Probability; //T
74                          inGraph.bayesianNet.SetNodeDefinition(node.nodeName, probabilitiesDef);
75                      }
76                  }
77              }
78
79
80              inGraph.bayesianNet.UpdateBeliefs();
81          }
82      }
83      catch (Exception exc)
84      {
85          Console.WriteLine("Could not load graph: " + exc.ToString());
86      }
87
88  }
```

In lines 14-21 new *SMILE* library instance is created, *SampleCount* is set to 5000 and a sampling algorithm is chosen based on the combo box which is placed in Bayes server GUI. *SampleCount* tells how many iterations the algorithm will do before returning probabilities.

Nodes are added in lines 24-33. One needs to use node names instead of node *IDs* because *string* identifiers are necessary in SMILE library. Outcome values need to be set as well. These can be any *string* like '*0*','*1*' or '*true*','*false*'. However, consistency is required. Once an outcome value is set one needs to stick to the chosen notation.

In lines 36-49 one adds arcs from the descendants list and from line 52 to 77 conditional probabilities are added. Refer to *BayesianLib.cs*:processSingleGraph(Graph inGraph) for full source code. *CPTs'* format is described in section 3.5.1.

3.5.2 Bayes client technologies

Bayes Client was written in C# using *Silverlight* technology from *Microsoft*. It does not reference any other libraries. Visual elements are defined in *XAML* language. Bayes Client references *BayesServerService* which is a SOAP web reference to Bayes Server.

Silverlight technology imposes some domain rules. Appropriate XMLs are mentioned in section 3.1.5. The "last resort" solution is to install *IIS* (*Internet Information Server*) from *Microsoft* and provide *clientaccesspolicy.xml* and *crossdomain.xml* in the root of the domain on port *80* (*localhost:80/clientaccesspolicy.xml* and *localhost:80/crossdomain.xml*). Some implementations of Silverlight in Internet browsers prefer this solution. Bayes server provides both security XML files in the root of the domain on its own so the web service should work out-of -the-box.

3.6 Bayes Server and Client manual

Server binaries, client content and a "*thin client*" such as a web browser is required to use Bayesian tool. In order to accomplish steps in section 3.6.2 the following needs to be done first:

- execute server binaries. Wait for its full initialization and check SOAP as well as REST addresses. One can check whether the server is working by entering "*http://127.0.0.1:8080/BayesServer/GetGraphLis* from a web browser and waiting for a successful response.
- place client content on a web server (or in a local directory) and open page "*ClientBayes.html*".
- check client access policy according to 3.1.5 if there is no communication between Silverlight and BayesServer.

3.6.1 Basic functionality

Basic functionality of Bayesian tool includes:

- conducting inference in Bayesian networks based on available graphs
- importing Bayesian networks in BS internal format: *.graph
- importing Bayesian networks in WEKA's BIF format (<BIF VERSION="0.3">)
- serving many users at once - every user has a personal lists of graphs
- user identification based on IP address
- the ability to download MPF and best VOI tests
- the ability to use the tool in a "*thin client*" such as a web browser

3.6.2 Manual

After completing preliminary actions one can move on to the inference. Bayes Client GUI is described in section 3.6.3. Open up your web browser and choose a graph from the combo box entitled "*Graph*". Bayesian network will be loaded with probabilities of events displayed. Color of nodes has a meaning as described in section 3.4. You can observe how the probabilities are distributed now. Whether you choose which test to run from the distribution or follow hints displayed in orange circles is up to you. Active tests aren't checked and executed tests are grayed out. You can execute the test by clicking on the appropriate combo box.

One can also control the inference with REST calls as described in section 3.1.6. Actually cross control with SOAP and REST is possible if one always fires up *GetGraph* before *AccomplishTest*. BayesServer treats these two interfaces with the same priority.

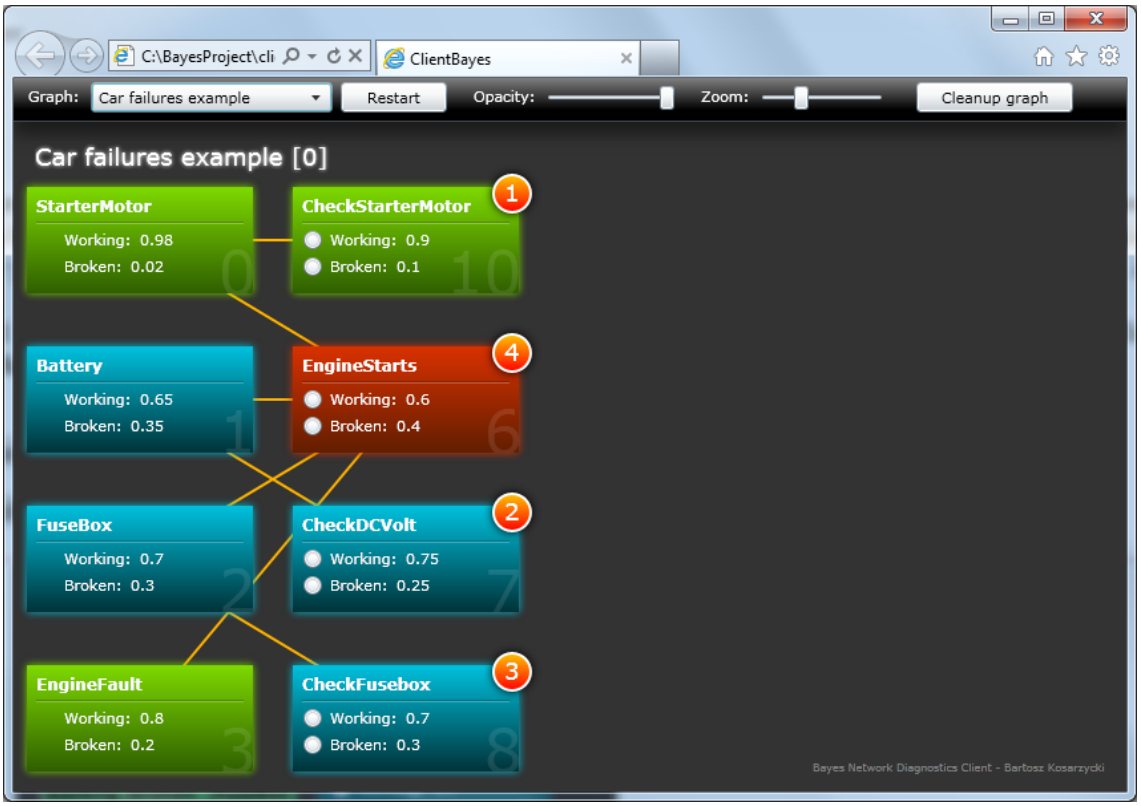


FIGURE 3.8: Bayes Client GUI

3.6.3 Bayes Client user interface

Graphical representation used by Bayesian Client is described in chapter 3.4. The BC GUI looks as follows:

Functionality:

- Bayesian networks can be chosen from the combo box visible in the upper left corner
- the opacity of nodes can be changed with a slider called "*opacity*"
- the slider "*zoom*" changes nodes' size
- nodes can be dragged about to accomplish desired network layout
- one can execute tests by clicking on combo boxes
- hints are displayed in orange circles in the upper right corner of each node. These are recommendations as to which test should be run first. The sequence is downloaded from server via *GetBestVOITests()* described in section 3.1.4. The lower number, the more lucrative the test is.
- nodes' colors have meaning as described in section 3.4.
- there is a node's id displayed in gray in the right corner of each node
- "*Cleanup graph*" button results in resetting zoom, opacity and nodes' position settings
- Conditional probability tables can be displayed after right-clicking on the appropriate node

3.6.4 Bayes Server user interface

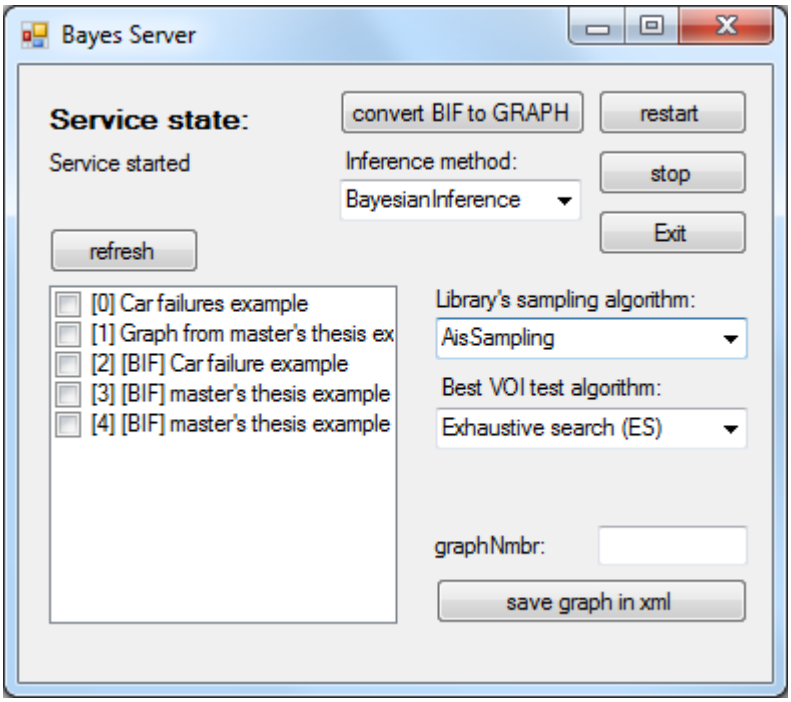


FIGURE 3.9: Bayes server GUI

The main feature controls of the server are placed in the upper-right corner of the *GUI*. One can *restart*, *stop*/*start* and *exit* the server. The "*convert BIF to GRAPH*" button converts files in BIF format (e.g. from WEKA) to Bayes Server's internal format. The process is described in section 3.3.6.

The "*Inference method*" combo box changes internal algorithms used in Bayesian server. One can choose to use the simple Bayesian inference or use sampling algorithms which are implemented in the SMILE library (refer to section 3.5.1). The "*Library's sampling algorithm*" combo box selects the internal algorithm used in SMILE library.

Bayes server implements different types of best VOI test selection algorithms. To change the one being used select an option from "*Best VOI test algorithm*" combo box.

To display the current list of available graphs one can click the "*refresh*" button. Selecting the check box enters appropriate number in the "*graphNmbr*" edit box. One can save the denoted graph with "*save graph in xml*" button.

There is a "*Service state*" label in the upper-left corner which displays the current state of the service - it can be *started* or *stopped*.

3.6.5 VOI tests and MPF ranking

Both rankings described in this section can be downloaded at any time of the diagnostic process through the use of REST/SOAP methods described in section 3.1.3 and 3.1.4.

Value of Information test ranking (VOI) is intended to minimize the diagnostic steps to isolate faults [17]. The decrease in the number of steps in the diagnostic process is crucial as it is assumed that the execution of tests takes much resources. This is not only about computational power but

more importantly about physical resources spent on performing tasks: time, money and the use of specialised tools. In other words VOI intend to minimize the cost of achieving the correct diagnosis through smart sequencing of tasks.

Diagnosis in Bayesian network is actually a differential diagnosis where current information suggests several candidates with high probability, to be confirmed or rejected.

One can calculate the lucrativeness of tests through measuring the entropy before and after their execution. This difference of entropy is called "*mutual information*" that the test carries along [17]. Mutual information captures the dependence between the faults and observations so when these are independant, the mutual information equals zero. The bigger the mutual information, the more dependant faults and observations are. Obviously executing tests with zero mutual information is useless.

Constructing VOI ranking is a hard computational problem. It is impossible to construct a static VOI ranking that would stay accurate throughout the reasoning [17]. One has to compute it after the execution of every new test as the test *adds new information* to the Bayesian network which means that current fault probabilities play a role. Such selection is called *myopic* which closely approximates optimal [17].

VOI test recommendation are displayed in Bayes Client as orange circles in the upper-right corner of available tests' nodes. The algorithms which were used in the creation of best VOI test rankings are described in section 3.2.3.

Most Probable Faults ranking is a simple list of failures that can be displayed to the user. It is constructed by taking nodes of a graph which are parts (have no parents) and sorting them in a descending $P(\neg X)$ order. MPF ranking is implemented as Bayes server can be used with a non-graphical client. In such a situation downloading MPF ranking is a substitute to Bayes client's network visualisation and tells which fault is the most probable one. Consequently there is no use for *GetRankingOfMostProbableFaults()* call in Bayes client and it was not implemented in it.

3.6.6 Multiple users

Bayes server can work with multiple clients. In the current implementation user is distinguished based on IP address. This results in the inability to run multiple instances of BC on a single machine. This implementation has many conveniences, however. These are described in section 4.

BS can work with multiple clients thanks to its dynamic list of graphs. Every user has a cloned list of Bayesian networks and his actions have no effect on other clients.

3.6.7 Console log

Server has a console that logs all actions called by users. This enables easy debugging as well as crash diagnosis. Clients are identified by their IP address. Every log line contains:

- Current time stamp
- IP address of the client
- Name of the called method

Sample console log:

```
1  Host: YOURHOST
2  REST&SOAP hosts opened - everything OK
3
4  REST interface addresses:
5  http://127.0.0.1:8080/BayesServer/GetGraphList
6  http://127.0.0.1:8080/BayesServer/GetGraph/graphNumber=0
7  http://127.0.0.1:8080/BayesServer/AccomplishTest/graphNumber=0&testNumber=1&working=true
8  http://127.0.0.1:8080/BayesServer/GetRankingOfMostProbableFaults/graphNumber=0
9  http://127.0.0.1:8080/BayesServer/ResetCalculations
10 http://127.0.0.1:8080/BayesServer/GetBestVOITests/graphNumber=0
11
12 SOAP interface addresses:
13 http://127.0.0.1:8081/?wsdl
14 http://127.0.0.1:8081/clientaccesspolicy.xml
15 http://127.0.0.1:8081/crossdomain.xml
16
17 Service call log:
18 ----------------
19 10:29:12 PM Client: 127.0.0.1 called GetSilverlightPolicy
20 10:29:12 PM Client: 127.0.0.1 called GetFlashPolicy
21 10:29:12 PM Client: 127.0.0.1 called GetGraphList
22 10:29:40 PM Client: 127.0.0.1 called GetGraph
23 10:29:40 PM Client: 127.0.0.1 called ResetCalculations
24 10:29:40 PM Client: 127.0.0.1 called GetBestVOITests
25 Requested test no: 3, state: True
26 10:29:44 PM Client: 127.0.0.1 called AccomplishTest
27 10:29:44 PM Client: 127.0.0.1 called GetGraph
28 10:29:44 PM Client: 127.0.0.1 called GetBestVOITests
```

Sample inference using Bayes Client

Figure 3.10 presents sample reasoning using Bayes Client. One starts by executing *CheckStarterMotor* test which comes out to be positive, so the starter motor is working. However the try to start the engine fails (*EngineStarts* test). The engine can fail to start because of the following parts: *StarterMotor*, *Battery*, *FuseBox* and because of the internal engine failure. In the next step one checks the battery by measuring DC voltage and the test is positive (*CheckDCVolt* test). At this point in reasoning there are only two candidates for failure: the *FuseBox* and the *EngineFault*. One can easily rule out FuseBox failure by executing *CheckFuseBox* test which is also encouraged by best VOI test ranking (the recommendation is displayed in the orange circle in the upper-eight corner of *CheckFuseBox* node). In the end there is only one fault possible with enough probability - the *Engine fault*. This ends the reasoning.

It is worth mentioning that the network lacks nodes 4-5. This is possible thanks to *isEmpty* property of nodes described in section 3.3.2. The network in figure 3.10 lacks the *ABS* and *BrakeFluid* nodes which were cut off to simplify the reasoning. One has to remember that crucial nodes cannot be cut off and that the edge list has to be modified (refer to section 3.3.2 for details).

FIGURE 3.10: Sample inference using Bayes client

3.7 Implementation final remarks

This chapter describes what has been successfully done in the Master's thesis' implementation and what could be improved. Encountered difficulties are described here as well.

The implementation of Bayes server lacks session IDs and users are identified based on IP address as mentioned in section 3.6.6. This is good for debugging as one can use SOAP and REST interfaces interchangeably. Introducing session IDs would also add one additional parameter to all SOAP and REST commands. Adding session implementation would not be hard, however.

The XML formats used in communication are a direct result of object-XML mapping and are used for SOAP and REST communication. The same format is used, however, when one imports a graph in Bayes server's internal format (BIF import is also possible - 3.3.6). These formats contain some additional and duplicated information such as - ancestors and descendants lists when only one of these is necessary to represent a graph. There is also a "parents list" near every CPT list and every row of this table contains outcome values that the Bayes client just displays and does not validate. This was handy for implementation of any *string* as an outcome value. In other words, the GRAPH structure which is described in section 3.3.2 contains redundant information that speeds up computations and eases data display.

There were some problems with *SetNodeDefinition()* function from SMILE library due to insufficient documentation. The library propagates probabilities in a different way as well. These issues were resolved successfully.

The *isEmpty* property described in section 3.3.2 enables the user to cut off parts of a graph in order to simplify reasoning. This can be done when the user finds out that a certain node has no effect on the real failure diagnosis. When part of a graph is cut off one does not loose node's properties and CPTs. Descendants list has to be rebuilt however. One could introduce a mechanism that would enable automatic list rebuild from GUI when the node is cut off or a graphical edition tool for GRAPH files.

It would be useful to move all the functionality in Bayes server GUI to Bayes client. It would require API change and introduction of new combo boxes inside *BC*. After successful implementation it would be possible to import a *BIF* file, save and load GRAPH files and select algorithms from Silverlight. *BS* GUI could be completely removed then.

3.8 Acknowledgments

The author of this work gratefully acknowledges the contribution of Dariusz Dwornikowski for his suggestions and materials on Bayesian networks as well as proof-reading of the entire work.

3.9 C# code of the algorithms used

3.9.1 Bayes server

Source code can be found in the attached CD.

- *Graph.cs* - contains the implementation of Bayesian inference algorithm
- *BIFConverter.cs* - contains code for importing files in *WEKA's* BIF format
- *BayesianLib.cs* - contains code used for integrating with *SMILE* library

3.9.2 Bayes client

Source code can be found in the attached CD.

- MainPage.xaml.cs - main window class

- ConditionalTable.xaml.cs - conditional table implementation
- NetworkGraph.xaml.cs, NetworkGraphEdge.xaml.cs, NetworkGraphNode.xaml.cs - Bayesian network graph implementation

Chapter 4

Conclusions

Bayesian tool's implementation was finished according to the assumed schedule. This allowed thorough documentation and testing with exemplary data.

As a result of transparent *API* the system was easily integrated with preexisting *IT-SOA* framework [1]. Thanks to the merge of Bayesian tool the *IT-SOA* system allows not only monitoring and management of services but the diagnosis of the failure's root causes as well.

All the functionality planned in the project was successfully implemented. Moreover it was expanded in many areas, such as:

- the import of graphs in *BIF* format in Bayesian server
- dynamic, eye-catching Bayesian networks' representation in Bayesian client

During the implementation of *BT* many useful technologies were used. The communication between modules is done with the help of self-describing *XMLs* and the client's *GUI* is written in *Silverlight's XAML* language which makes it extremely easy to make future changes. Industry standard for Bayesian networks is used for graph import - *BIF* version 0.3. With the newest web technologies there is no need for installation of the software, as a *thin client* (such as an Internet browser) is sufficient to use the Bayesian tool.

BT makes it extremely easy to choose among many kinds of reasoning algorithms and proves experimentally that sampling algorithms can be used in real-world computations with little (or no) quality degradation.

Thanks to REST/SOAP model usage one has a possibility to implement one's own GUI/console client or service which can be used with the Bayesian reasoning server.

Appendix:Abbreviations

Abbreviation	Meaning
BN	Bayesian Network
BI	Bayesian inference
CPT	Conditional Probability Table
VOI	Value of Information test
MPF	Most Probable Fault ranking
XML	Extensible Markup Language
IP	Internet Protocol
BS	Bayesian Server
BC	Bayesian Client
BIF/XMLBIF	Bayesian Interchange Format
GUI	Graphical User Interface
SOAP	Simple Object Access Protocol
REST	Representational State Transfer
SOA	Service-oriented architecture
BOD	Blue Screen of Death
SDK	Software Development Kit
XAML	Extensible Application Markup Language
IIS	Internet Information Services
BIF	Bayesian Interchange Format
ES	Exhaustive Search
ESn	Exhaustive Search (ES) based only on negative execution of tests
API	Application Programming Interface
XAML	Extensible Application Markup Language

TABLE 4.1: Abbreviations

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