Evaluation of the SRA tool using Data Mining Techniques

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Abstract. This paper describes a validation approach of a socio-technical design support system using data mining techniques. Bayesian Belief Networks (BBN) are used to assess human error and system failure [13] based on a variety of high-level operational scenarios. The System Reliability Analyser (SRA) tool automates the process by iteratively manipulating the BBN model. Data mining techniques are employed in order to identify whether the initial assumptions embedded in the system reliability model are met by results from scenario-based testing.

1. Introduction

This paper addresses the problem of validating the behaviour of a design support system, the System Reliability Analyser (SRA), using data mining techniques. This is the continuation of our work that identified potential system failures in complex socio-technical systems [8], [14]. This approach enables reliability evaluation of costly socio-technical system designs such as the command and control rooms of military vessels before being fully operational. Due to the criticality of the decisions made by the system we need to be assured that its embedded logic directly maps our initial assumptions. BBNs however are complex causal models, very difficult to test against experimental data [11]. Validation strategies are to run scenario data sets against the model to test whether the assumptions implemented in the model are valid compared with known examples. However, this approach is tedious and time consuming due to the vast amount of data produced. Automation of this task is achieved through data mining. Data mining enables us to test the system based on the results that it produces and the rules that we incorporated in it. Additionally it can discover assumptions not explicitly defined in the initial model. For this process we employed three techniques: relevance analysis, association rules and classification.

2. SRA Tool

The tool composed of three main components, the Session Controller, the Reliability Analyser and the Visualiser. The Session Controller implements an algorithm that runs a set of scenarios against a high-level model of the system design. The Reliability Analyser component runs the BBN model for each task-step of a scenario with an exhaustive combination of all the model input parameters. Finally the Visualiser provides a visual summary of all the runs for a set of scenarios. This enables different designs to be compared and problem areas to be identified, i.e. role/technical component combinations which show low potential reliability. This paper focuses on validating the Reliability Analyser component of the tool and how it assists analysts identify potential problems in socio-technical system designs.

BBNs are graphical networks that represent probabilistic relationships between variables. They offer decision support for probabilistic reasoning in the presence of uncertainty and combine the advantages of an intuitive representation with a sound mathematical basis in Bayesian probability [10]. BBNs are useful for inferring the probabilities of events which have not as yet been observed, on the basis of observations or other evidence that have a causal relationship to the event in question [3].

However due to the size of BBN models it is difficult to ascertain influence of variables from Bays Theorem based itself, and this is the reason we employed data mining techniques.

The BBN that we developed describes the various influences on human error [9] and predicts the probability of system error based on a variety of input evidence [12]. According to Reason [11], human error is defined as "all the occasions in which a planned sequence of mental or physical activities fails to achieve its intended outcome, and when these failures can not be attributed to the invention of some change agency".

The systems reliability analyser (SRA) tool that we developed enables the assessment of system reliability based on automated manipulation of the BBN model using high-level scenarios [8].

The first problem is converting scenarios which are narrative stories of event sequences into a form that can be automatically analysed by the SRA. To escape from the problem of hand crafting every scenario sequence, we employed generic tasks as reusable models of activity [1] [14]. This enabled scenarios to be coded more rapidly by specialising task models.

At the end of each scenario phase the tool displays for each task step the total number of scenario runs that satisfied the reliability requirement specified by the user, in a histogram. The overall system reliability is measured by the total surviving scenarios from each batch of tests. This enables two alternative designs to be compared; however, problem areas in the design are also pinpointed by task steps with a low number of survivors.

3. SRA Validation Methodology

In order to be confident that the SRA tool generates results that are based on the assumptions and rules that we identified in the domain, it is important to validate the BBN model based on realistic scenarios. Due to the high volume of data (for one scenario composed of 4 phase with six task steps in each phase the tool generates $4*6*3^{12}$ records in the database) generated by the tool we employed data mining techniques to validate it.

Data mining is a methodology that assists in uncovering hidden data patterns and searches for relationships in vast amounts of data, such as the relationship between noise and level of human error [6]. Data mining aims to extract valuable but "hidden" knowledge [7].

In our case we are using data mining as a means of validating the behaviour of the BBN model. Using the BBN model we simulate high-level scenarios with a large number of variations in environmental conditions then use data mining techniques to test whether our initial assumptions and rules that we embedded in the model were met.

The validation process is composed of the following steps: Select representative scenarios from the domain, Convert scenarios in SRA format, Simulate the scenarios using SRA, employ the following data mining techniques on the generated results.

Relevance Analysis

The purpose of relevance analysis is to rank the available input parameters of the model based on their relevance to one of the model's output parameters (level of system error field in the table-target parameter) or with each other.

Association Rules

Association rules describe how often two or more facts co-occur in a data set. For instance an association rule that might be extracted from the system reliability simulation results is: "most human agents with low task knowledge perform poorly on the radar operation task if the sea state is bad". In our case we employ association rules in order to identify causal associations in our model.

Classification

Classification technique partitions large quantities of data into sets of common characteristics and properties.

4. Conclusions /Discussion

In order to validate the SRA tool we conducted a case study to assess the level of system reliability in the combat subsystem of a naval offshore patrol vessel. The results of the simulation are investigated by the three techniques to identify data patterns that would help us validate the model behaviour.

In the case study we employed a typical air to surface missile attack scenario. The System Reliability Analyser tool is used to identify potential system failures of the command and control subsystem of an offshore patrol vessel. Each scenario run is input into the BBN model which determines the probability of system error for each run. If the probability of error is lower that a pre-specified threshold then the run survives (pass). The details of all scenario runs are stored in a database for the model validation. The data mining techniques are employed to identify relationships between the status of the scenario runs (failed/passed), the level of system error and the input parameters.

Based on the results of the data mining techniques we identified that the main assumptions we initially made about human error have been partially satisfied. However, the analysis exposes behaviours of the model that had not been expected. These behaviours give further understanding of our initial assumptions and enable as to improve the accuracy of the BBN model. An interesting observation made from the results is that sea state (environmental parameter) was not a major influence on system error. According to domain experts, sea state is a major influence on human error, depending on the level of training of the crew and the time it has been on duty. This assumption was implemented in the BBN model during its construction, however all analyses revealed that sea state plays a minor role in system error. The reason is due to the number of intermediate nodes between the sea state and system error node. In order to overcome this deficiency of the model it is necessary to alter its causal diagram.

Relevance analysis identified inconsistencies between our initial assumptions and the results for the workload and duty time of the crew, and usability of technological components and management culture. Association rules analysis identified rules that exist in the model but were not initially defined when building the model. Finally, classification tree analysis pinpointed problems with crew motivation, task complexity and agent ability nodes and assisted in the identification of critical paths in the decision tree structure of the model.

Based on these observations it is necessary to alter the BBN model's NPT tables and parts of the causal diagram in order to match our initial assumptions. Data mining techniques have been proven beneficial in validating the SRA tool, by identifying whether the behaviour of the embedded BBN model satisfies the initial model rule specification. From the results of the relevance analysis, association rules and classification we conclude that our initial assumptions were partially met. This leads us to the next phase of our model development which aims to overcome the deficiencies identified through this analysis.

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