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# An Intuitive Dashboard for Bayesian Network Inference

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**Abstract.** Current Bayesian network software packages provide good graphical interface for users who design and develop Bayesian networks for various applications. However, the intended end-users of these networks may not necessarily find such an interface appealing and at times it could be overwhelming, particularly when the number of nodes in the network is large. To circumvent this problem, this paper presents an intuitive dashboard, which provides an additional layer of abstraction, enabling the end-users to easily perform inferences over the Bayesian networks. Unlike most software packages, which display the nodes and arcs of the network, the developed tool organises the nodes based on the cause-and-effect relationship, making the user-interaction more intuitive and friendly. In addition to performing various types of inferences, the users can conveniently use the tool to verify the behaviour of the developed Bayesian network. The tool has been developed using QT and SMILE libraries in C++.

## 1. Introduction

In recent years, Bayesian Networks/Directed graphical models [1] are being applied in diverse fields, such as computational biology [2], ecology [3], defence [4], and robotics [5]. Bayesian networks (BNs) provide an intuitive way of representing and visualising the structure of a probabilistic model. They aid in solving numerous learning and inference problems in complex models conveniently.

A typical BN  $\mathcal{G} = \{V, E\}$  constitutes  $V$  vertices that are connected by  $E$  directed edges. Let  $\mathbf{x}$  be a set of discrete random variables, denoted by  $\mathbf{x} = \{x_1, x_2, \dots, x_K\}$ . In a graphical model, each vertex represents a random variable or a set of random variables, while the directed links express causal probabilistic relationships between the variables. Specifically, depending on the direction of the edge, we denote certain nodes as parent or child with respect to other nodes. For example, in Figure. 1, node  $x_3$  is the parent of  $x_4$  and child of  $x_1$ . The joint distribution of directed graphs is given by:

$$p(\mathbf{x}) = \prod_{n=1}^N p(x_n | \mathbf{x}_{\pi_n}) \quad (1)$$

The joint distribution is the product of the conditional distribution of each node  $n$  conditioned only on its parents  $\mathbf{x}_{\pi_n}$ . In the example shown in Figure. 1, the joint distribution factorises as  $p(x_1, x_2, x_3, x_4) = p(x_1)p(x_2|x_1)p(x_3|x_1)p(x_4|x_3)$ . There are numerous BN software packages



such as Hugin<sup>1</sup>, Genie<sup>2</sup>, BayesiaLab<sup>3</sup>, Netica<sup>4</sup> which could be used for developing, inferring and learning of the network.

Although, such BN packages provide a good graphical interface for users who design and develop Bayesian networks for various applications, the intended end-users of these networks, who could be from a non-technical background (*e.g.* airport operators, physicians, chemists), may not necessarily find such an interface appealing and comfortable to use. At times, comprehending such networks could be overwhelming, particularly when the number of nodes in the network is large (more than 10). Furthermore, performing inferences on such a network could be even difficult as it may not be straightforward to perceive how changes to a particular node value will affect the rest of the nodes it is connected to (*e.g.* as a parent or child node).

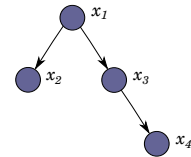


Figure 1: A toy example of a Bayesian Network.

To illustrate this phenomenon, we consider a fairly complex real-world BN model recently proposed for wayfinding at airports [6]. The Wayfinding Bayesian Network Model (WBNM) explored the effects that human and environmental factors have on effective wayfinding in airports. It investigated the main influences on these factors as well as the most important elements of communication, the built environment, and what effect if any, do gender, airport familiarity and anxiety have on effective wayfinding in airports. A screen-shot of the model rendered using Genie software package is shown in Figure 2. Using the package, the end-user can infer the posterior probabilities of the nodes of the network (shown for few nodes at the bottom-right in Figure 2). It is evident that such a visualisation could be cumbersome while doing inferences. For example, if the end-user changed the evidence of one of the nodes and wanted to see its impact on the other nodes of the network, the user has to carefully track the node connections to see the influences. Such a process could be painstaking and time-consuming for the end-user.

To circumvent the above-mentioned limitations, this paper presents an intuitive dashboard, which provides an additional layer of abstraction, enabling the end-users to easily perform inferences over the BNs. The developed tool is called INSIGHTS, as it aims to pro-actively aid the user to clearly understand the model and the underlying causal relationships between its various factors (nodes). The tool organises the nodes based on the cause-and-effect relationship, making the user-interaction more intuitive and friendly. The rest of the paper is organised as follows: the details of the developed tool INSIGHTS v1.0, is provided in Section 2, while Section 3 discusses the results and capabilities of the developed tool followed by conclusion in Section 4.

## 2. INSIGHTS

The proposed tool INSIGHTS has the ability to run in real-time and automatically compute and display the marginal probabilities of the states of the nodes in a more intuitive manner than that shown in Figure 2. Screen-shots of the dashboard are shown in Figure 3. Such an intuitive dashboard enables the end-users to easily perform various types of inferences on the model. The tool internally uses SMILE<sup>5</sup> and QT libraries [7] to perform the Bayesian inferences and GUI visualisations, respectively. The SMILE library has a set of APIs that not only read and edit BNs but also perform inferences on them. Most of the inference algorithms are based on the approximate stochastic sampling techniques.

INSIGHTS requires the end-user to load two input files - BN model and ancillary text files. The BN model file is developed by using one of the existing Bayesian software packages such as Genie. The current version of the tool is able to parse standard BN file formats supported by Hugin,

<sup>1</sup> <http://www.hugin.com/>

<sup>2</sup> <http://genie.sis.pitt.edu>

<sup>3</sup> <http://www.bayesia.com/>

<sup>4</sup> <http://www.norsys.com>

<sup>5</sup> <http://genie.sis.pitt.edu/index.php/downloads>

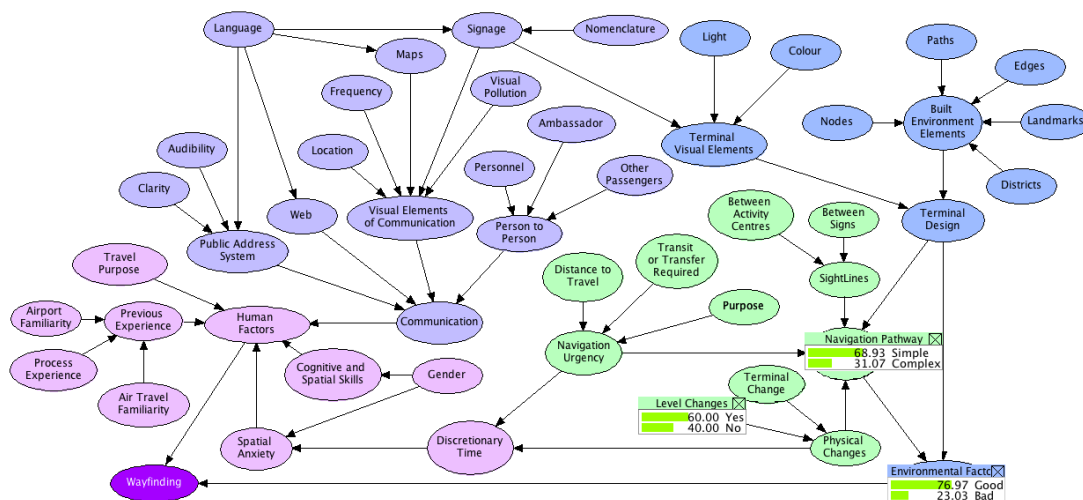


Figure 2: An example of current visualisation of the wayfinding model [6] using a popular BN software package Genie. End-users can inspect the posterior probabilities of the various nodes of the network, which get overlaid on top of the nodes as depicted at the bottom-right corner. Such a visualisation is hard to comprehend and perform inferences on the network.

Genie and Netica. The whole BN network is parsed and stored internally as a tree structure. Based on end-users response (typically button clicks), relevant sections of the BN are displayed on the dashboard. The other input, ancillary text file, contains the list of key nodes one wishes to monitor and will be displayed on the dashboard at the start-up as shown in Figure 3(a).

### 3. Results

The wayfinding model [6] was initially developed in Genie. All the necessary parameters such as the node states and relevant probability tables (conditional and marginal) were defined. As mentioned earlier, INSIGHTS requires two input files for its execution. The BN file representing the wayfinding model and an ancillary text file, which in this context, contained the name of one node 'Wayfinding' as it is the key node that the end-user is interested in (see Figure 2).

On execution of INSIGHTS, the user sees a dashboard displaying the key nodes (depicted as push-buttons) along with the marginal probabilities of their pre-defined states (represented by progress bars) as shown in Figure 3(a). Here the node 'Wayfinding' has two states 'Effective' and 'Ineffective' with values of 81% and 19%, respectively. By clicking the 'Wayfinding' push-button located to the left of the progress bars leads to a new screen similar to Figure 3(b), which displays its two parents, namely 'Environmental' Factors and 'Human Factors, along with the marginal probabilities of their states.

The users can further drill down to see all the other nodes that influence the value of wayfinding. Furthermore, they can set new evidence for any of the nodes and inspect their impact on the other nodes that are linked to them (either directly or indirectly) by clicking on the 'New Evidence' button (see the pop-up window in Figure 3(b)). The 'Reset' button is used to clear the evidences. Such a feature, could be conveniently used by researchers to validate the behaviour of the developed model under various values of evidences, particularly at the extremities, and simulate 'what-if' scenarios.

The navigation display panel on the left side of the screen shows how the user has traversed the network to reach to the current display screen. Similarly, the blue text line at the bottom of the screen reveals the buttons clicked to reach to the current display screen. Both features get updated dynamically every time user clicks the buttons. The '<<' button at the bottom is used to roll back a step. As a result, with mere clicks the user could traverse the whole network

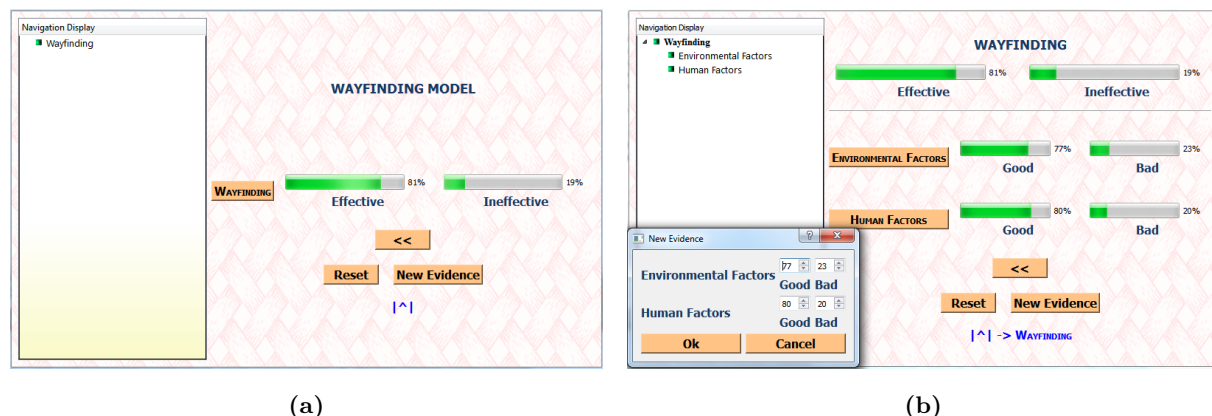


Figure 3: Screen-shots of INSIGHTS at various points during its operation. (a) Screen shot at start-up, showing the posterior probability of the resultant node measuring the wayfinding effectiveness of a building [6]. (b) obtained after clicking the ‘Wayfinding’ push-button. It displays the two factors affecting the wayfinding - ‘Environment Factors’ and ‘Human Factors’, along with their state-probabilities. As noted, the end-user can also add new evidence and inspect how it could affect the performance of the overall network.

in an intuitive manner, without looking at the actual BN model (consisting of nodes and arcs). Clustering of nodes in this manner (parent-child relationship) will provide better understanding of the BN model and to study the influences between its nodes.

#### 4. Conclusion

Current BN packages typically overlay the results on top of the graph making it difficult for end-users to see patterns, trends, or exceptions in the model results. The proposed tool INSIGHTS provides an easy and intuitive interface for end-users to perform inferences on the BNs. These visualisations allow end-users to see the results, interdependencies and influences between factors in the BN model in a more lucid manner.

In summary, the developed tool INSIGHTS has 3 key benefits. It can: (i) organise and render the nodes of the network based on a cause-and-effect relationship; (ii) be used as a diagnostic tool to find the underlying causes of a certain phenomenon/behaviour conveniently; and (iii) perform various ‘what-if’ scenarios by adding new evidence quite easily. As part of future work, we would like to extend this tool to automatically learn marginal/conditional probability tables from the relevant data for each node variable of the network.

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