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August 7, 2011

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Visualizing and Understanding Large-Scale Bayesian Networks

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Abstract

Bayesian networks are a theoretically well-founded approach to represent large multi-variate probability distributions, and have proven useful in a broad range of applications. While several software tools for visualizing and editing Bayesian networks exist, they have important weaknesses when it comes to enabling users to clearly understand and compare conditional probability tables in the context of network topology, especially in large-scale networks. This paper describes a system for improving the ability for computers to work with people to develop intelligent systems through the construction of high-performing Bayesian networks. We describe NetEx, a tool developed as a Cytoscape plugin, which allows a user to visually inspect and compare details concerning multiple nodes in a Bayesian network while maintaining awareness of their network context. It uses a “thought bubble line” to connect nodes in a graph representation and their internal information at the side of the graph. The tool seeks to improve the ability of experts to analyze and debug large Bayesian network models, and to help people to understand how alternative algorithms and Bayesian networks operate, providing insights into how to improve them.

Introduction

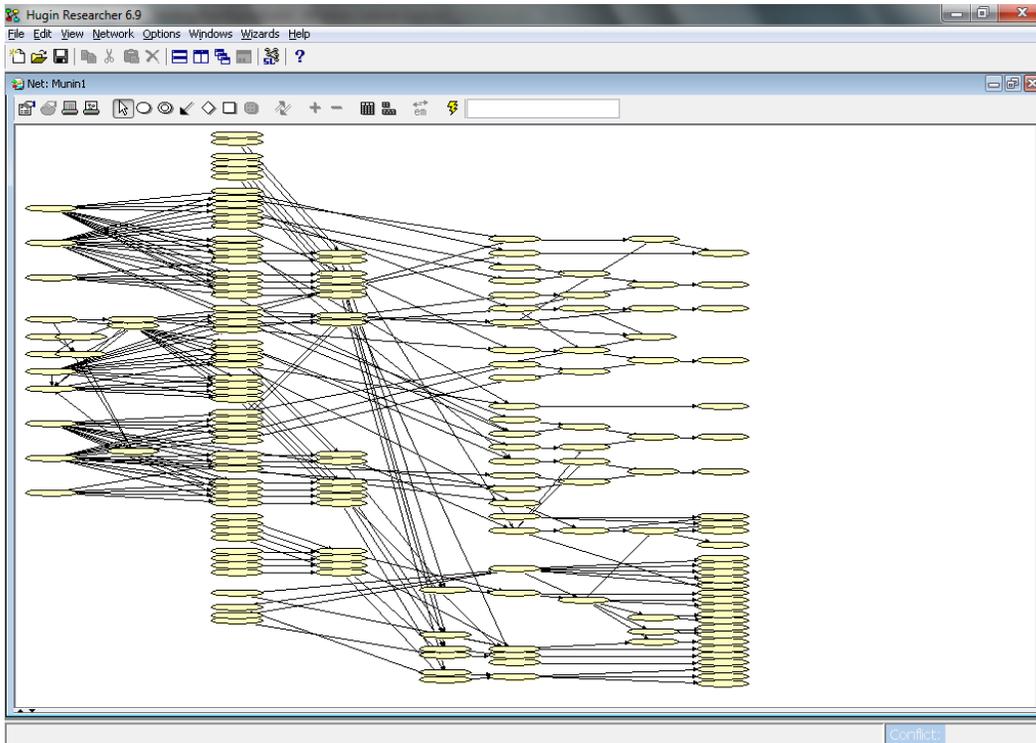
Large-scale probabilistic graphical models are becoming increasingly important across a broad range of scientific, technical, and business areas. Bayesian networks, for example, have been useful in domains such as medical diagnosis (Andreassen et al. 1989; 1991; Shwe et al. 1991), system health management (Rish, Brodie, and Ma 2002; Mengshoel et al. 2008; Ricks and Mengshoel 2010; Mengshoel 2010), information theory (McEliece, Mackay, and Cheng 1998; MacKay 2002), and reliability (Langseth and Portinale 2007).

Bayesian networks are graphical models for encoding the full joint probability distribution of variables in a compact form (Pearl 1988; Darwiche 2009). A Bayesian network consists of two components: a directed acyclic graph (i.e. a graph with directed edges and no cycles) and a set of conditional probability distributions (CPDs). Each node in the

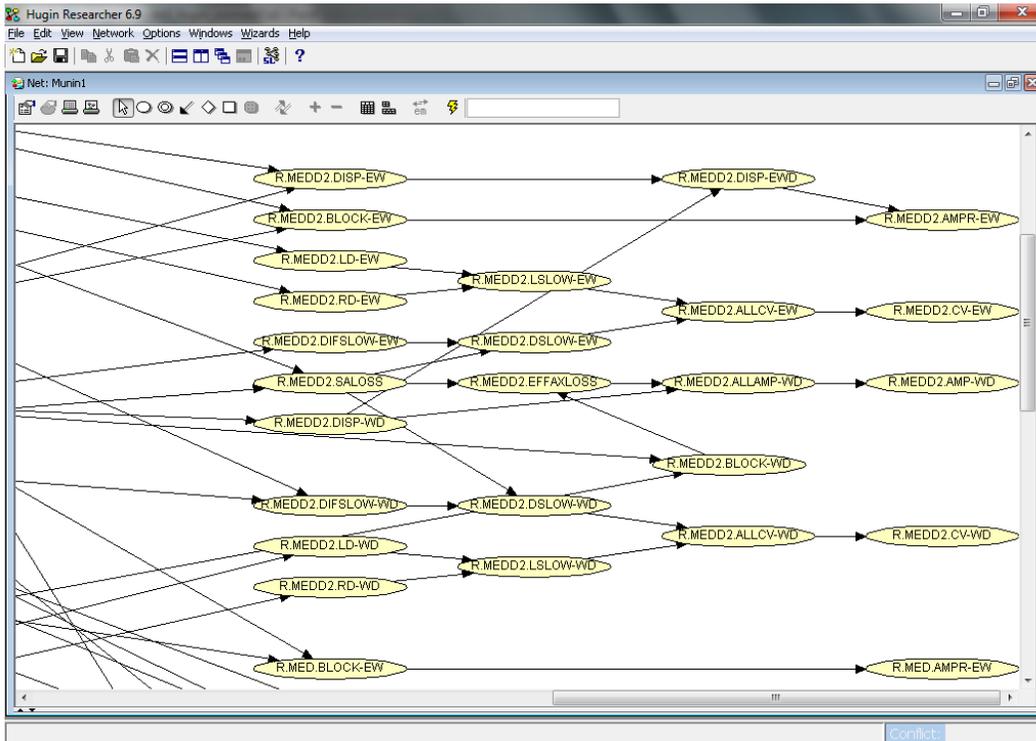
graph represents a random variable (i.e. an attribute of the data), while edges represent dependencies among the variables. CPDs describe the probability for the value of each node given the value of its parents, and are very often represented as conditional probability tables (CPTs, see Figure 2(A)).

As part of manually constructing a Bayesian network, or validating a Bayesian network that has been induced using machine learning, it is useful to visually inspect it. Structure, states, and CPTs are all important in a Bayesian reasoning architecture, and research has been done to understand how each of these aspects can be effectively visualized. Interesting work has been done in developing algorithms to compute an optimal layout for the network (Marriott et al. 2005; 2011). The use of visual properties such as color, size, and thickness of nodes and edges to convey information about relative influence of variables, in terms of probabilities, has been investigated as well (Koiter 2006; Williams and Amant 2006; Zapata-Rivera, Neufeld, and Greer 1999). Tools have also been proposed to present compact representation of CPTs (Chiang et al. 2005; Wang and Druzdzel 2000). Other relevant work has focused on using animation for visualizing causal relationships (Kadaba, Irani, and Leboe 2007) and building verbal descriptions to provide the user with more insights into the computation of explanations (Yap, Tan, and Pang 2008).

The challenges associated with understanding how a Bayesian network works as well as visualizing it increase significantly as the size and connectivity of the network increases. While several software techniques for visualizing and analyzing Bayesian networks have been developed, popular current tools¹ for Bayesian network modeling focus on inference/learning procedures, with little support for flexible interactive visualization. First, they have difficulty visualizing large-scale networks, such as the one shown in Figure 1. Second, they force the user to perform visual search to locate interesting information, which can be like looking for a needle in a haystack even for Bayesian networks with a few hundred nodes, depending on display size and resolution. Also, current tools offer very little support for displaying the network structure along with the underlying data (e.g., time



(a) Whole view: the global structure of the network is perfectly visible, but it is impossible to read labels of individual nodes.



(b) Zoomed view: node labels are readable, but the global structure of the network is lost.

Figure 1: When large networks such as *Munin1* are visualized, it is very hard to read labels of individual nodes (a), unless a significant level of zooming is adopted (b).

series) used to build the network. Analysts would benefit from improved interactive and visual support for debugging the network structure and tuning CPT parameters, which are fundamental stages in the process of Bayesian network modeling.

In this paper we describe novel interactive visualization techniques for Bayesian network, implemented in our software tool NetEx, which is developed as a Cytoscape (Shannon et al. 2003) plug-in. The visualization techniques of NetEx target large-scale Bayesian networks. Our techniques are inspired by and extend techniques from other areas of network visualization and analysis (Butkiewicz et al. 2008; Baldonado, Woodruff, and Kuchinsky 2000; Collins and Carpendale 2007; Weaver 2004; Plumlee and Ware 2006). NetEx allows low-level, focused analysis while preserving context awareness by displaying both an overview and detailed view of the network, and anchoring CPTs to the network view with dashed lines. NetEx also supports integration of additional data related to a node, such as time series sensor readings, and facilitates comparisons by showing data from multiple nodes into a single data box. The techniques described in this paper will allow better interactive analysis of Bayesian networks and comparison of CPTs within them, besides better understanding of the machine learning algorithms sometimes used to build networks.

Background and related work

A Bayesian network, whose graph structure $\mathbf{G} = \langle \mathbf{V}, \mathbf{E} \rangle$ often reflects a domains causal structure, is a compact representation of a joint probability table (Pearl 1988). Typically, each random variable (or node) $X \in \mathbf{V}$ has a finite number of states $\{x_1, \dots, x_m\}$ and is parameterized by a conditional probability table $P(X|Pa(X))$, where $Pa(X)$ is the set of nodes $Pa(X) = \{Y \in \mathbf{V} s.t. (Y, X) \in \mathbf{E}\}$, named the parents of X . By providing evidence to a subset of nodes, the answer to various interesting probabilistic queries can be computed, including the marginal posterior distribution over one or more nodes, or most probable explanations over nodes for which no evidence is provided.

Previous research on Bayesian network visualization has typically focused on two important problems: mapping relevant data attributes into visual properties of the network (such as node size, color and position) to make it easily understandable by the viewer, and supporting navigation in large conditional probability tables.

Zapata-Rivera et al. (1999), for example, showed that cause-effect relationships can be made clearer by adopting a top-down layout from causes to effects, and computing node hues by combining the colors of parents. They also investigated the use of node position to highlight strong dependencies between variables, as well as node size and saturation to convey information about marginal probabilities.

Koiter (2006) proposed a very powerful static visualization of the properties of a network by rendering edge thickness as an indicator of the strength of interaction between nodes, combined with edge color to indicate the sign of the correlation coefficient. Williams and Amant (2006) presented a method to emphasize evidence by adding a colored

border to nodes corresponding to observed variables. Kadaba et al. (2007) studied the visualization of causal semantics through animated representations.

As for elicitation of conditional probability tables (CPT), *GenIe* & *SMILE* (Druzdel 1999) provides users with bar chart and pie chart distributions of the probabilities for a selected column. Wang and Druzdel (2000) proposed two graphical views, namely the Conditional Probability Tree (CPTree) and the shrinkable Conditional Probability Table (sCPT), that proved to be useful for navigation in large CPTs. A different approach was presented by Chiang et al. (2005), who represent CPTs using heat maps, where numerical cell values are replaced by colors in order to facilitate comparisons and reduce space issues.

The systems discussed above are great at presenting a static visualization, but provide little help for interactive focused comparisons of different parts of the network. These valuable analysis tools can be very useful to explore local cause-effect relationships in relatively small networks, but do not allow a curious debugger to rummage through a large network asking specific questions. Despite all the interesting works discussed above, popular current tools for Bayesian network modeling focus on editing, learning, and inference procedures, offering less support for effective user-driven exploration of large-scale networks. Current tools, such as *Hugin* (Andersen et al. 1989), potentially require large visual search to locate isolated interesting information. As Figure 1 shows, it is very hard to read node labels when a large network such as *Munin1* (Andreassen et al. 1989) is visualized (Figure 1(a)). Traditional zooming techniques implemented in current tools allow the user to see details, but at the price of losing the global structure of the network (Figure 1(b)). These tools also typically lack support for easily comparing underlying data (e.g. time series) which might provide a richer understanding of the model.

Bayesian network visualization with NetEx

Large-scale Bayesian networks, including their development and performance, are a key issue in artificial intelligence (Neil, Fenton, and Nielson 2000; Przytula, Isdale, and Lu 2006; Mengshoel, Wilkins, and Roth 2006; Mengshoel, Poll, and Kurtoglu 2009; Mengshoel 2010). What is meant by “large-scale”? For the purpose of this paper, we are concerned with scalability as it pertains to visualization and user interaction. This is different from computational scalability, which is also very important but discussed elsewhere (Mengshoel, Wilkins, and Roth 2006; Mengshoel 2010).

To be precise, we define a BN to be large-scale if the complete BN and all its node labels are not simultaneously visible on the computer screen. Once node labels are no longer visible, one needs to (for example) zoom in to understand what a particular node represents, and after zooming in the big picture understanding may get lost. This effect is illustrated in Figure 1. Given this definition of large-scale, and depending on the display technology used, a BN is large-scale once it contains 100s or 1,000s of nodes and edges. All the networks discussed and displayed in this paper are large-scale according to the above definition.

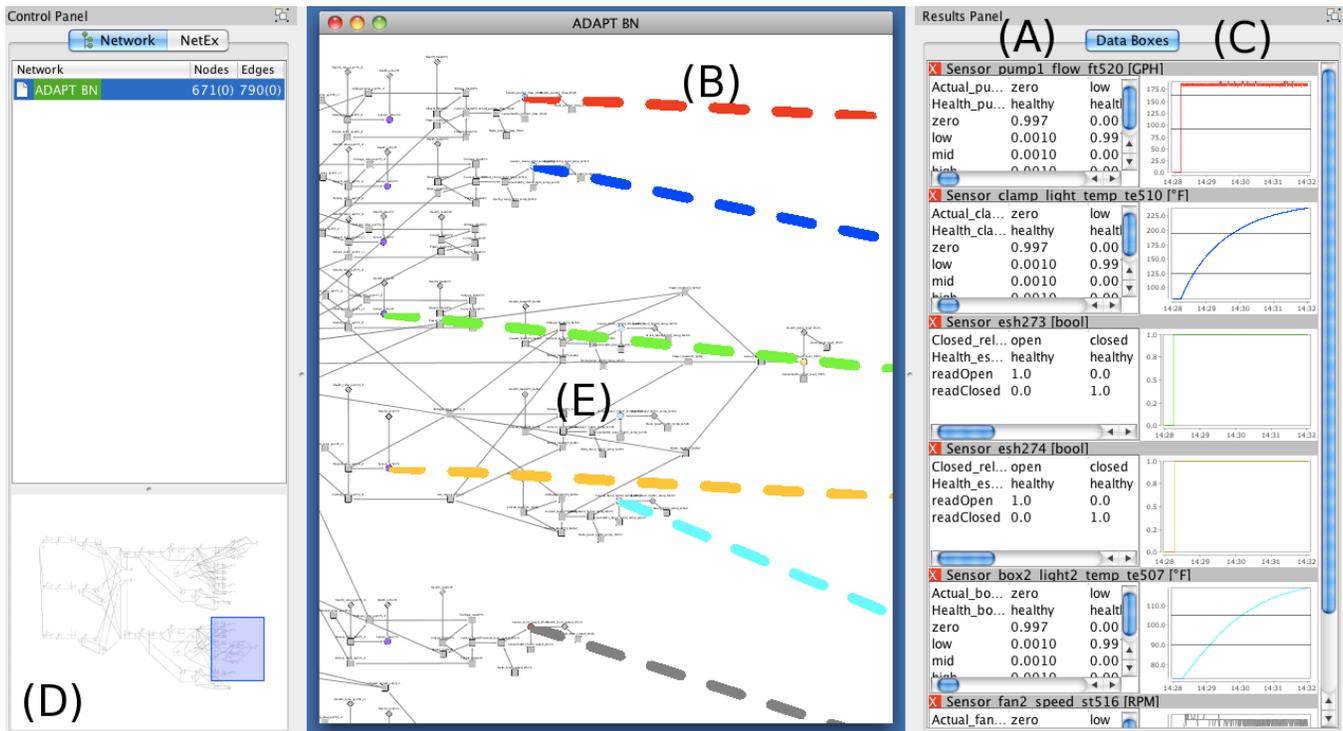


Figure 2: Bayesian network visualization in NetEx: (A) CPTs, (B) bubble anchors, (C) integrated time series display, (D) overview, and (E) detailed view. Anchoring the CPTs to the network view with large dashed bubbles allows low-level detailed analysis and comparison while preserving the overview of the network and reducing clutter.

In this section we describe in detail the visualization techniques for Bayesian networks implemented in our software tool NetEx (Figure 2), which targets large-scale Bayesian networks. First, conditional probability tables are, in NetEx, shown in *data boxes* attached to the network view with a line of bubbles which anchors each box to the node it is related to. The representation is *multi-focus* as it allows the user to open multiple boxes to focus on different nodes simultaneously. Second, NetEx supports integration of additional data related to a node, such as time series sensor readings, into a CPT data box. Third, NetEx facilitates comparison of different nodes by allowing data from multiple nodes to be merged into a single box by dragging a box and dropping it over another one (*drag&merge*). Finally, the tool provides overview+detail (Cockburn, Karlson, and Bederson 2008), simultaneously displaying both an overview and detailed view of the network.

CPT bubble anchors

NetEx promotes interactive visual exploration, allowing users to select nodes in the network with a mouse, and to show the corresponding CPTs (Figure 2(A)) using on-demand data boxes attached to the network view with a line of bubbles anchoring the CPT $P(X|Pa(X))$ to the node X (Figure 2(B)).

This joint use of CPT data boxes and anchors presents a focus+context concept (Cockburn, Karlson, and Bederson 2008), as the user is allowed to focus on some particular

node and then continue the exploration of the network and focus on another node without losing contact with the previous node. The change in representation level is reinforced by bubbles that are inspired by the way cartoons show what a person is thinking. The use of bubbles instead of straight lines distinguishes between graph edges and anchors.

Multiple nodes can be selected at the same time, either by dragging a bounding box around them or by clicking on each separately. A single “s” key stroke expands the selected nodes by showing the corresponding data boxes in a panel next to network view (Figure 2(A)). If more boxes are opened than can be displayed, a scroll-bar is used to scroll the panel, with the bubble lines following the movement of the boxes in the display. When one of the boxes is closed by clicking the “x” at the top left corner, the remaining boxes are rearranged to fill the gap for the sake of minimizing screen space usage.

This feature, which can be seen as an extension of the probes proposed by Butkiewicz et al. (Butkiewicz et al. 2008) to Bayesian networks, is useful to all systems that have multiple levels of representation: many analysis tasks require the user to inspect multiple nodes at the same time in order to easily compare them.

Showing data boxes in a separate panel as discussed above reduces the space available for the network view. For this reason, NetEx also allows the user to display the boxes over the network with a “o” key stroke (Figure 3), and to move them or change the network view through zooming and pan-

ning to focus on various parts of the network while preserving the context. The drawback of this approach is that data boxes overlaying the network view can hide important details in some situations. NetEx allows the user to choose the solution which is more appropriate to the specific analysis task.

Integrated time series display

NetEx supports integration of additional data related nodes into the data boxes to provide the user with a richer representation of the model. Figure 2(C) shows an example in which the CPT of a node representing a sensor in an electrical power network is coupled with a time series plot showing the sensor readings over time. Similarly to many other cases, the node's states are obtained through discretization of the continuous range of values provided by the sensor. NetEx enriches the time series representation by displaying horizontal lines at the values corresponding to the thresholds used to discretize the node's states.

This feature is especially useful when the thresholds are automatically computed using some machine learning algorithm. Similar nodes might have the same set of states (i.e. *low* and *high*), but very different thresholds. This information, which is especially helpful while comparing multiple nodes, is not easily accessible with other current tools.

CPT merging

NetEx facilitates comparison of different nodes by allowing data from two nodes to be merged into a single box just by dragging a box and dropping it over another one (*drag&merge*). Figure 3 shows an example of application of this technique. A different color is associated with each of the nodes to be compared. Both the line in the plots and the bubbles are painted with this color to allow for immediate association of nodes with corresponding data. Original colors are preserved to help the user maintain association between nodes and data, even when the latter is moved into a different box.

This feature is available when nodes share the same CPT structure, i.e. the states of the nodes and their parents are exactly the same. Each cell in the merged CPT shows the difference between the original values of the two nodes for that cell. This is very useful when debugging a network, as similar nodes are usually supposed to have similar CPTs, and spotting non-zero values in the merged CPT is quicker than comparing pairs of unspecified values in the two original CPTs.

Data box merging also helps the user compare time series plots of similar nodes. By looking at the combined data box in Figure 3(b), for example, it is easy to realize that the considered nodes have very similar though not exactly identical plots. The difference between two plots is much harder to appreciate when separate individual boxes are shown (Figure 3(a)).

Network overview

NetEx provides overview+detail (Cockburn, Karlson, and Bederson 2008), simultaneously displaying both an

overview (Figure 2(D)) and detailed view (Figure 2(E)) of the network. Zooming and panning allow the user to restrict attention to a particular area of the graph which is visualized in the detailed view. NetEx allows the user to explore data at a desired level of detail without losing the complete picture of the network and thus preserving the capability of orienting even when a small area is selected in the detail view. Though common in other areas of network visualization (Cockburn, Karlson, and Bederson 2008), to our knowledge this technique has not been applied to Bayesian networks before.

Applications

The techniques described in the previous section were implemented by developing a visualization tool in the form of a Cytoscape² (Shannon et al. 2003) plug-in. Cytoscape is a software platform for complex network analysis, offering a basic set of visualization features that can be expanded through additional plug-ins.

This section demonstrates how NetEx can help analyze different large-scale Bayesian networks. As examples, we use a Bayesian network for fault diagnosis of the ADAPT electrical power network (Mengshoel et al. 2010), and *Diabetes* (Andreassen et al. 1991), a well known network used for medical diagnosis. For the purpose of comparison, we use Hugin (Andersen et al. 1989), one of the most popular current tools for Bayesian network modeling.

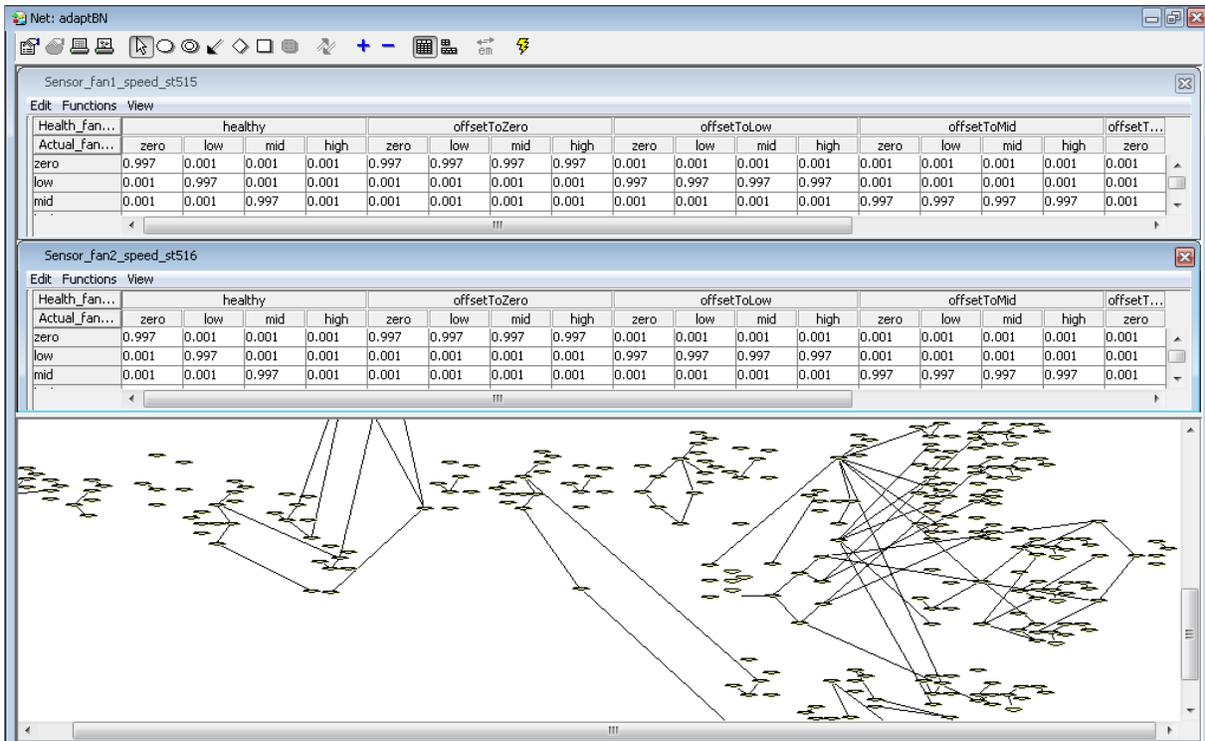
ADAPT Bayesian network

ADAPT (Poll et al. 2007) is an electrical power system created and used for experimentation at the NASA Ames Research Center, representative of real-world electrical power networks found in aerospace vehicles. It has capabilities for power storage, distribution, and consumption, containing batteries, electromechanical relays, circuit breakers, and different kinds of loads, such as pumps, fans, and light bulbs. Several sensors are available, measuring voltage, current, relay position, temperature, light intensity, and liquid flow.

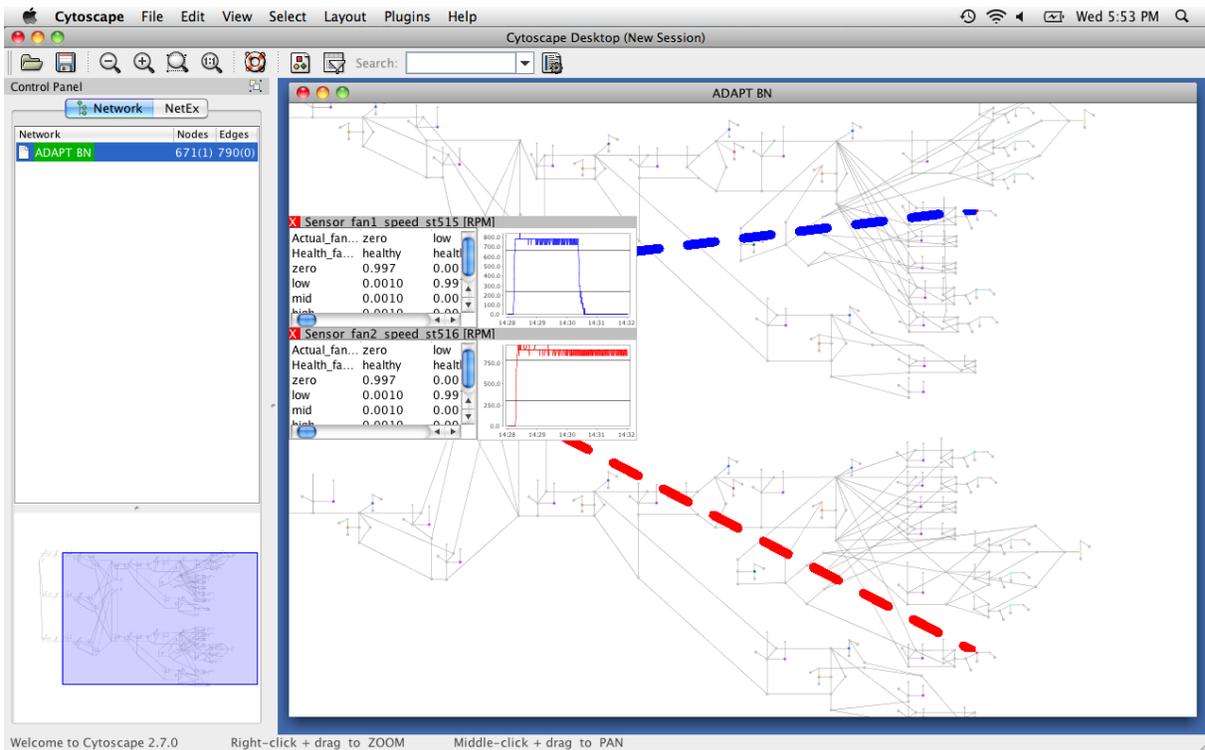
The ADAPT Bayesian network (BN) (Mengshoel et al. 2010) is a model of the electrical power network (EPS) used for automatic fault diagnosis. Its structure reflects the components and causal structure of the EPS, and explicitly represents the health of each component and sensor using random variables, supporting different diagnostic queries. The ADAPT Bayesian network, shown in Figure 4, has 671 nodes and 790 edges. According to the definition provided above, this network is large-scale as it is impossible to read labels on nodes.

NetEx supports integration of time series sensor readings together with the conditional probability tables (Figure 4(b)). The time series representation is enriched with horizontal lines showing the thresholds used to discretize the states of the corresponding node. This information, which might be helpful while comparing multiple nodes, is not easily accessible with other software tools (Figure 4(a)).

²<http://www.cytoscape.org>

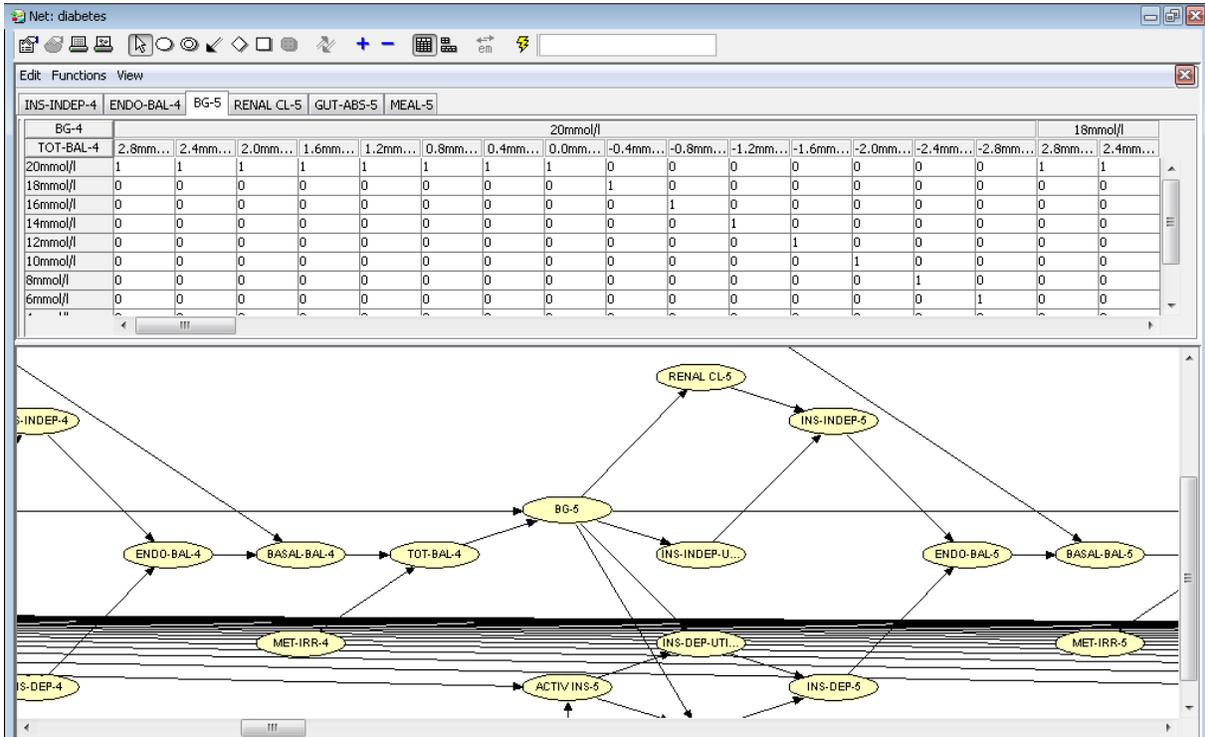


(a) Hugin: since there is no visual link between CPTs (top) and corresponding nodes (bottom), it might be hard for the user see the connection between a node and its CPT and to compare multiple nodes.

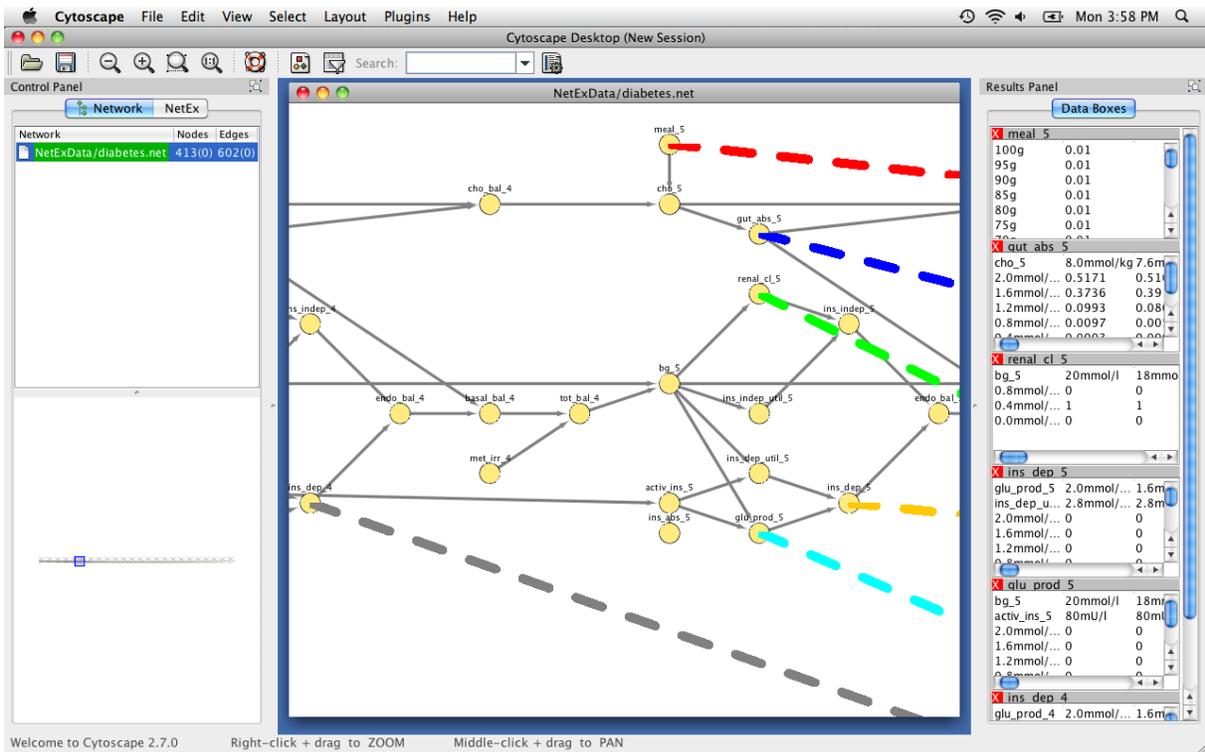


(b) NetEx: colored bubble lines facilitate association of CPTs with respective nodes, and time series plots provide more insights about the CPTs, allowing for deeper understanding of the network and facilitated comparison of nodes.

Figure 4: Visualization of the ADAPT Bayesian network using (a) Hugin and (b) NetEx.



(a) Hugin: there is no visual link between CPTs (top) and corresponding nodes (bottom); after zooming, the complete picture of the network is lost.



(b) NetEx: colored bubble lines facilitate association of CPTs (right) with respective nodes (middle); the overview window (left) helps the user keep oriented while exploring the network.

Figure 5: Visualization of the *Diabetes* Bayesian network using (a) Hugin and (b) NetEx.

Diabetes Bayesian network

The *Diabetes* Bayesian network (Andreassen et al. 1991) is a model of blood glucose in diabetic subjects that can be used for advising insulin dose adjustment. The network, having 413 nodes and 602 edges, is shown in Figure 5. While we only show zoomed-in views, it is not possible to read labels in a zoomed-out view.

Current tools such as Hugin provide no visual link between the conditional probability tables and the corresponding nodes, requiring the user to match CPTs with nodes based only on the node labels (Figure 5(a)). This may potentially require the user to visually inspect all the nodes of the network. Moreover, since the complete structure of the network is lost after zooming, it is hard for the user to orient while exploring the network. NetEx, on the other hand, facilitates association of CPTs with respective nodes through colored bubble lines and provides a network overview allowing the user to restrict attention to a particular area of the graph while simultaneously displaying the image of the whole network (Figure 5(b)).

Conclusion

This paper demonstrates NetEx, an interactive network analysis tool designed to aid in understanding and developing large-scale Bayesian networks. The described visualization techniques allow detailed analysis and comparison of multiple Bayesian network nodes while providing awareness of the overall network structure. While many Bayesian network tools focus on inference, NetEx provides the analyst with interactive visualization techniques to help identify problems, such as discrepancies in the model, including CPT parameter errors or faulty network structure.

The value of this work is in celebrating the ability for computers to work with people to create intelligent systems through the construction of high-performing Bayesian networks. We seek to improve the ability of knowledge engineers and experts to analyze and debug models of greater complexity and with larger node counts. We expect NetEx will help the artificial intelligence and other communities explore more deeply how alternative algorithms and Bayesian networks operate, thus providing insights into how to improve them.

Acknowledgments

This material is based, in part, upon work by Michele Cosalter, Ole J. Mengshoel and Ted Selker supported by NSF grants CCF-0937044 and ECCS-0931978.

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