In Anthony Jameson, Cécile Paris, and Carlo Tasso (Eds.), *User Modeling: Proceedings of the Sixth International Conference, UM97.* Vienna, New York: Springer Wien New York. © CISM, 1997. Available on−line from http://um.org.

Assessing Temporally Variable User Properties With Dynamic Bayesian Networks

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Abstract. Bayesian networks have been successfully applied to the assessment of user properties which remain unchanged during a session. However, many properties of a person vary over time, thus raising new questions of network modeling. In this paper we characterize different types of dependencies that occur in networks that deal with the modeling of temporally variable user properties. We show how existing techniques of applying dynamic probabilistic networks can be adapted for the task of modeling the dependencies in dynamic Bayesian networks. We illustrate the proposed techniques using examples of emergency calls to the fire department of the city of Saarbrücken. The fire department officers are experienced in dealing with emergency calls from callers whose available working memory capacity is temporarily limited. We develop a model which reconstructs the officers' assessments of a caller's working memory capacity.

1 Introduction

Bayesian networks (cf. Pearl, 1988) are able to handle uncertainty in an elegant way and have already been successfully used in user modeling (cf. Jameson, 1996b). They are mostly applied to the assessment of a user's properties which remain unchanged during a session. However, user properties often vary with time, e.g., in student learning situations or in cases where short-term cognitive states have to be assessed. Schum (1987) points out several problems arising due to the temporal change of such situations, e.g., the same evidence can have different meanings at different time points.

The following issue is therefore of general interest: How can temporally variable user properties be estimated with Bayesian networks?

Modeling temporally variable properties demands the creation of adequate and tractable dynamic Bayesian networks (DBNs). We identify and categorize the dependencies to be modeled, e.g., dependencies between temporally variable and temporally invariable properties. We describe how dynamic probabilistic networks (including dynamic Bayesian networks) have been applied to related problems and show how to adapt the solutions to our problems. We propose some general schemes for modeling the dependencies and discuss their assets and drawbacks.

There are many other approaches for representing temporal relationships within a probabilistic framework. For example, Conati and VanLehn (1996) solve a student modeling task by building

* The preparation of this article was supported by the German Science Foundation in its special Collaborative Program on Resource-Adaptive Cognitive Processes (SFB 378), project B2, READY. We wish to thank Anthony Jameson, Anselm Blocher, Susanne van Mulken, and the two anonymous reviewers for valuable suggestions on earlier versions of this paper.

a Bayesian network incrementally. In this way the network represents the current state of the user. This approach lacks an explicit representation of time. Cooper et al. (1988) use a probabilistic approach for diagnosing diseases. The temporal dependencies are represented directly in the conditional probabilities. This approach already contains many ideas used in DBNs, but the distinction between different types of variables is not clear, e.g., between variables evolving over time and non-evolving variables.

We show how the proposed techniques are used in the dialog system READY (**Re**source-**A**daptive **D**ialog S**y**stem, Wahlster et al., 1995). READY has to help a person $\mathcal{P}$ during an emergency. To minimize $\mathcal{P}$'s cognitive load, READY adapts its dialog behavior among other things to $\mathcal{P}$'s available working memory capacity (AWMC), which strongly varies over time. [1] Estimating $\mathcal{P}$'s AWMC involves uncertainty, because it cannot be directly observed.

We will show how to construct a DBN for assessing $\mathcal{P}$'s AWMC which is based on the results of an empirical study. We interviewed firemen at the Saarbrücken fire department who are experienced in dealing with emergency calls from people whose AWMC is temporarily limited. The DBN reconstructs the inferences of the firemen.

In the next section, we will describe the scenario of our example domain and identify the occurring dependencies. Then we will show how to model the dependencies in a DBN.

2 Dependencies in the Example Domain

People who place emergency calls to the fire department are usually anxious and distracted. Therefore their AWMC is temporarily limited. The task of a fire brigade officer is to gather details about the incident as fast as possible in order to react properly.

In an empirical study an emergency call dialog was played to the officers of a fire department who served as subjects. At particular times the tape was stopped and questions were asked about the dialog. By retrospective thinking-aloud (cf. Ericsson and Simon, 1993) the subject's assessments of the caller's properties were acquired. Based on these assessments, we identified the dependencies in the domain (cf. Jameson, 1996a) which are partly depicted in Figure 1. In order to make the explanations in the following sections more clear, we use a very simple model, i.e., we have not used the sophisticated models developed in cognitive psychology.

External causes allow us to infer *internal causes* for a limitation of $\mathcal{P}$'s AWMC: The larger $\mathcal{P}$'s AMOUNT OF EXPERIENCE WITH EMERGENCIES and the smaller the SIZE OF EMERGENCY, the more probable it is that $\mathcal{P}$ has the ABILITY TO HANDLE THE SITUATION. The less $\mathcal{P}$ has the ABILITY TO HANDLE THE SITUATION, the more probable it is that there will be a higher level of ANXIETY.

On the basis of the internal causes, $\mathcal{P}$'s AVAILABLE WORKING MEMORY CAPACITY (AWMC) can be assessed. ANXIETY causes a temporary limitation of $\mathcal{P}$'s AWMC (cf. also Calvo and Eysenck, 1996). The same is true of INTOXICATION. The higher the DIFFICULTY OF A QUESTION and the lower $\mathcal{P}$'s AWMC, the greater is the probability of a bad QUALITY OF THE ANSWER (which constitutes *observable evidence*) of $\mathcal{P}$ to the question. BREATHING NOISE suggests a high level of ANXIETY. If the LOCATION OF THE CALL IS A BAR (indicated by the BACKGROUND NOISE OF A BAR) then there is a high probability that $\mathcal{P}$ is in a state of INTOXICATION, which is also indicated by a POOR ARTICULATION.

[1] The cognitive load of a user also has to be taken into account when presenting instructions or explanations (cf. Kashihara et al., 1995). Similarly, Horvitz and Barry (1995) point out that the cognitive load of a user has to be considered when displaying information for monitoring complex systems.

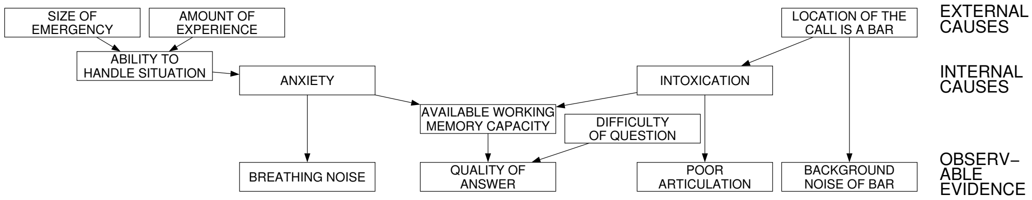

Figure 1. Dependencies in our domain (an arrow from A to B indicates that A influences B).

There are two types of user properties: *Static user properties* remain unchanged during the dialog, e.g., $\mathcal{P}$'s INTOXICATION.[2] *Temporally variable user properties* change over time, e.g., $\mathcal{P}$'s AWMC and ANXIETY. Perhaps $\mathcal{P}$ will calm down, i.e., $\mathcal{P}$'s ANXIETY will decrease. Or, the emergency may get worse and $\mathcal{P}$ may become more anxious. $\mathcal{P}$'s AWMC will also vary. It is possible that $\mathcal{P}$ is temporarily occupied with other things which also require working memory capacity.

It is very hard to predict how $\mathcal{P}$'s ANXIETY and AWMC will change over time. Observable evidence must be interpreted in order to obtain an accurate estimate.

In the following sections we will show how the described dependencies can be modeled by DBNs. Because of space limitations, we have to limit the presentation of the network to the most important parts.

3 User Modeling With Bayesian Networks

3.1 Static Bayesian Networks

A *Bayesian network* (BN) is a kind of probabilistic network (cf. Pearl, 1988).[3] A BN is a directed acyclic graph. Its *nodes* represent *random variables* consisting of a set of mutually exclusive and exhaustive propositions, called *hypotheses*. For each hypothesis the probability of being true is maintained. All these probabilities represent a *probability distribution*, called the *belief* of a node. The *links* between the nodes represent the dependencies between the propositions. Such a dependency is expressed by a *conditional probability table* (CPT).

For the *root nodes*, *a priori probabilities* must be defined. The belief of a node that is not a root node can be predicted from the beliefs of its *parent nodes*. *Observed evidence* for a node can be *interpreted* and used to recalculate its belief. Then the beliefs of its parent nodes are recalculated. This is repeated unless a node is a root node.[4]

Defining a BN implies tradeoffs, e.g., with respect to the granularity of the representation. The more fine-grained the representation, i.e, the more hypotheses the variables have, the more detailed but also the more costly the inferences will be.

After defining a BN it would be useful to *validate* the network, e.g., examine whether the inferences of the BN are comparable to the inferences of a domain expert. A *sensitivity analysis* (cf., e.g., Russell and Norvig, 1995, section 16.7) reveals the robustness of the inferences.

[2] Of course, this property remains unchanged only during a short period of time, e.g., during a phone call.
[3] Neapolitan (1990) and Charniak (1991) also provide introductions to Bayesian networks.
[4] This account is simplified. If there are nodes in the network which are connected via two or more paths, the network is *multiply connected* and requires more costly inference algorithms (cf. Pearl, 1988).

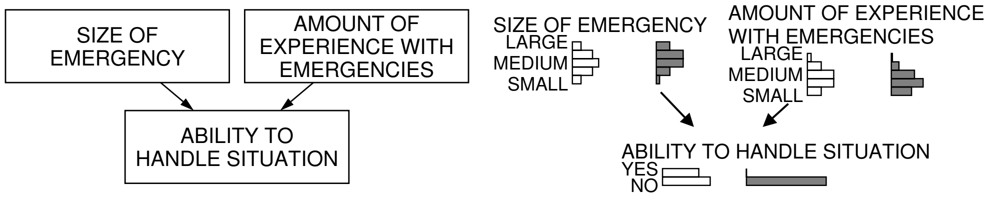

Figure 2. Static BN for processing of one observation.

Figure 2 shows a BN for estimating $\mathcal{P}$'s AMOUNT OF EXPERIENCE WITH EMERGENCIES.[5] The left-hand side of Figure 2 depicts the qualitative dependencies. They correspond to the upper left of Figure 1 in Section 2. The right-hand side of Figure 2 shows histograms depicting the belief of the nodes. The white histograms show the estimate in the beginning: SIZE OF EMERGENCY is estimated as most probably medium. $\mathcal{P}$'s AMOUNT OF EXPERIENCE WITH EMERGENCIES is regarded as most probably medium or slightly below medium. It is predicted that $\mathcal{P}$ will probably not have the ABILITY TO HANDLE THE SITUATION. Now assume we *observe* that $\mathcal{P}$ does not have the ABILITY TO HANDLE THE SITUATION (dark-shaded histogram). By interpreting this evidence, we conclude that $\mathcal{P}$ probably has a smaller AMOUNT OF EXPERIENCE and that the SIZE OF EMERGENCY is larger than we initially assumed (see dark-shaded histograms).

If we could observe $\mathcal{P}$ in a number of emergencies, we would be able to estimate $\mathcal{P}$'s AMOUNT OF EXPERIENCE with more certainty. Figure 3 shows a simple model. In our example in Figure 3 we observe that $\mathcal{P}$ fails to handle two situations. Therefore $\mathcal{P}$'s AMOUNT OF EXPERIENCE is assessed as quite small. The white histograms show the BN in the beginning and the grey ones after the interpretation of $\mathcal{P}$'s failure to handle Situation 1 (the dark-shaded ones in Situation 2).

If a static BN is defined in advance, there is a drawback. If the observations were interpreted one after the other, the interpretation of a new observation would lead to a reinterpretation of past observations, e.g., in Figure 3 the interpretation of $\mathcal{P}$'s inability to handle Situation 2 leads to a reinterpretation of the SIZE OF EMERGENCY 1. Such reinterpretations are not always useful. In our example we are interested only in assessing $\mathcal{P}$'s AMOUNT OF EXPERIENCE. In the next section we will show how to avoid the drawback by using DBNs.

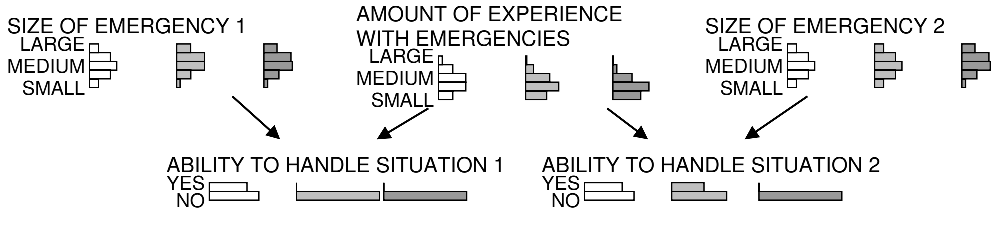

Figure 3. Static BN for processing of two observations.

[5] If these BNs were to be used for more than illustrative purposes, we would have to clearly define the meaning of variables like SIZE OF EMERGENCY. Spetzler and von Holstein (1975) propose a simple test: A clairvoyant should be able to predict the variable without requesting clarification of the meaning of the variable and its possible values.

3.2 Dynamic Bayesian Networks

A *dynamic Bayesian network* (DBN) is a kind of a *dynamic probabilistic network* (DPN). DPNs (cf. Dagum et al., 1992; Kjærulff, 1992; Nicholson and Brady, 1992; Tawfik and Neufeld, 1994) are networks which are able to model stochastic temporal processes.[6] For example, Dagum et al. (1992) used a dynamic network to forecast U.S. car sales in Japan. A typical application is locating a vehicle (cf., e.g., Nicholson and Brady, 1994; Forbes et al., 1995).

Typically, a *time slice* represents a snapshot of the temporal process. Usually there is a time slice representing the present (t), the past ($t - 1$) and if needed one for the future ($t + 1$).[7] The CPTs representing the dependencies between the time slices define the *state evolution model*. The objects represented by *dynamic nodes* evolve over time. *Static nodes* represent unchanging objects. We call nodes which exist in only one time slice *temporary nodes*. Usually the CPTs and the structure of the subnetwork remain the same within a time slice. However, Dagum et al. (1992) point out that unmodeled exogenous forces could lead to a deterioration of the model and require an update of the CPTs or possibly of the structure of the network.[8]

With *rollup* the DBN can be simplified: The subnetwork for slice $t - 1$ is removed after the subnetwork for slice t is established. Usually the dynamic nodes in t become root nodes and have to be assigned prior probabilities: The prior probabilities of a dynamic node D in t are defined as the belief of D in t before removing the subnetwork (cf., e.g., Russell and Norvig, 1995, section 17.5). Kjærulff (1992) generalizes this by combining several time slices to a *window of time slices*, i.e., the "present" is represented by a number of time slices. There are also *backward smoothing slices*, i.e., rollup is delayed. Similarly, there is also a number of *forecasting slices*.

In a DBN there are three types of dependencies: between dynamic and temporary nodes, between dynamic and dynamic nodes, and between static and dynamic nodes. In the following sections we will propose general schemes for modeling these dependencies and discuss the assets and drawbacks of the schemes.

Dependencies between dynamic and temporary nodes. In the simplest case, the child node of a dynamic node D is a temporary node T, e.g., an evidence node. For example, $\mathcal{P}$'s ANXIETY (D) is the cause of BREATHING NOISE (T). The dependency can be modeled adequately by the model $\mathcal{M}1$ depicted in Figure 4. Analogous modeling is employed by, e.g., Forbes et al. (1995). We will illustrate our model using the following example.

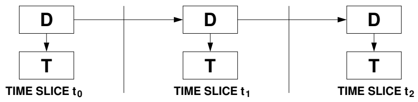

Figure 4. $\mathcal{M}1$: Modeling the dependency between a dynamic node D and a temporary node T.

[6] Instead of *dynamic networks*, some authors use the term *temporal networks*.

[7] The terms t, $t-1$, and $t+1$ represent relative descriptions of time slices, whereas t_1 or t_2 refer to absolute time slices, e.g., if the current time slice t is t_0, then slice $t + 1$ will be slice t_1.

[8] In some cases the probabilities are time-dependent (cf. Tawfik and Neufeld, 1994). Horvitz and Barry (1995) give an example in the domain of the space shuttle. If there is a propellant failure during burn, the probability that the engine will be damaged is higher the longer the burn continues.

Example 1: At the beginning of a phone call there is a lot of breathing noise. Subsequently it decreases, indicating that $\mathcal{P}$ is calming down.

Figure 5 shows a network for Example 1. For didactical reasons, we simplify the dependencies by assuming that node ANXIETY has no parents. Every time slice covers the same period. In time slice t_0 there is a lot of breathing noise, whereas in t_1 and t_2 there is little. The left-hand histograms in each time slice show the beliefs of the nodes before the interpretation of evidence, the right-hand ones after interpretation. We have to consider that $\mathcal{P}$'s ANXIETY evolves over time. In the example, $\mathcal{P}$ is very anxious during t_0. We can further deduce that $\mathcal{P}$ will probably calm down slightly from t_0 to t_1. This can be seen by comparing the dark-shaded histograms of ANXIETY in t_0 to the white ones in t_1. In Figure 5 $\mathcal{P}$'s ANXIETY in t_2 is regarded as probably low.

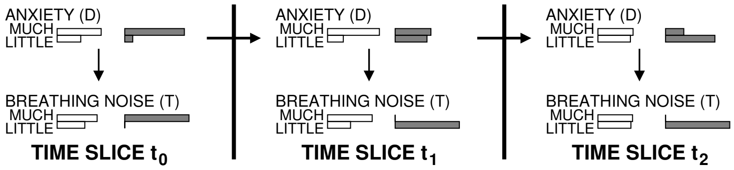

Figure 5. DBN according to the model $\mathcal{M}1$ for handling Example 1.

In Section 3.1, Figure 3 depicts a static BN for dealing with multiple observations which makes useless reinterpretations. To avoid this drawback Heckerman (1993) proposes a temporal definition of causal independence. Dynamic nodes are introduced in order to collect independent influences of several causes on an effect node. Jensen (1995a,1995b) also employs this idea.

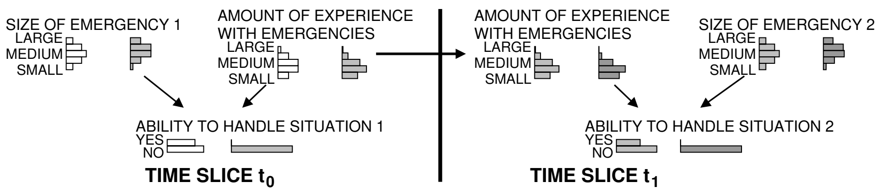

Figure 6. DBN for processing of observations.

If we apply this idea to our example, we have to collect the effects of the observations on $\mathcal{P}$'s AMOUNT OF EXPERIENCE, now modeled as a dynamic node. Figure 6 depicts the corresponding DBN. The dependency between AMOUNT OF EXPERIENCE in $t - 1$ and AMOUNT OF EXPERIENCE in t is defined in a way that the belief of these two nodes is the same. By applying rollup (not shown in Figure 6) at most two time slices exist at a given moment. In this way interpretation of an unlimited number of observations can be done very efficiently.

Dependencies between dynamic nodes. Sometimes a dynamic node D2 has another dynamic node D1 as a parent node. For example, $\mathcal{P}$'s AWMC (D2) depends on $\mathcal{P}$'s ANXIETY (D1). Both AWMC and ANXIETY evolve over time.

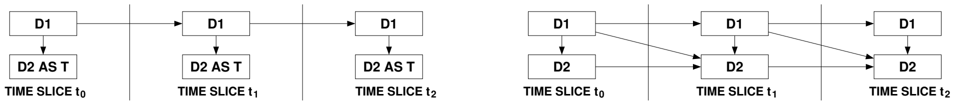

Figure 7. $\mathcal{M}2.1$ (left) and $\mathcal{M}2.2$ (right): Modeling the dependency between dynamic nodes D1 and D2. In $\mathcal{M}2.1$ dynamic node D2 is simplified as a temporary node T (D2 AS T).

In a simple modeling we can adapt the model $\mathcal{M}1$. D2, which is a child of dynamic node D1, is represented in a simplified way, *not* as a dynamic but as a temporary node T (see the model $\mathcal{M}2.1$ as depicted by the left-hand scheme in Figure 7). In each time slice a new instance of T is created by a prediction. There is no link between T in $t-1$ and T in t. T in $t-1$ influences T in t solely via their common parent nodes (D1 in $t-1$ and D1 in t). The prediction of T in t based on D1 in t will be less accurate than when it is additionally based on the estimate of T in the time slice before. We will illustrate the model with the following example, which is based on Example 1.

Example 2: At the beginning of a phone call there is a lot of breathing noise. Subsequently it decreases, indicating that $\mathcal{P}$ is calming down. In addition, $\mathcal{P}$ is asked three simple questions which $\mathcal{P}$ answers with very poor quality.

For didactical reasons we simplify the dependencies by not taking other causes for a reduction of $\mathcal{P}$'s AWMC than ANXIETY into account. In Figure 8 we show the results for Example 2 of a DBN modeled according to $\mathcal{M}2.1$. For reasons of space, DIFFICULTY OF QUESTION is not shown in Figure 8 and the following figures. In t_0 a lot of BREATHING NOISE indicates a lot of ANXIETY. Because of this and $\mathcal{P}$'s bad answer, $\mathcal{P}$'s AWMC is estimated as quite low in t_0 (see dark-shaded histogram). In t_1 AWMC has to be repredicted because it is represented as a temporary node. As can be seen by the white histogram in t_1 for AWMC, the result of the prediction is less accurate than the result obtained in slice t_0. In t_2, the little BREATHING NOISE indicates that $\mathcal{P}$ is calming down; therefore $\mathcal{P}$'s ANXIETY is estimated as lower in t_2 than in t_1 (see dark-shaded histograms). This leads to the questionable result that despite the poor answers there is a trend in ascribing approximately the same AWMC to $\mathcal{P}$ in t_2 as in t_1. (Strictly speaking there is even a slight increase.) This can be seen by comparison of the dark-shaded histograms of AWMC which indicate the state of the node after the interpretation of the bad answer. This is because AWMC depends solely on ANXIETY here and $\mathcal{P}$'s ANXIETY is estimated as probably low because of the limited BREATHING NOISE.

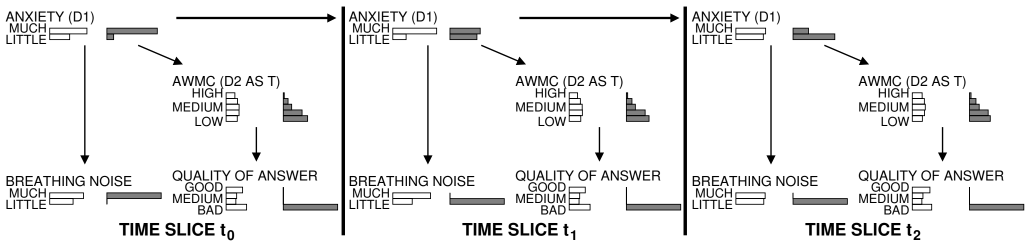

Figure 8. DBN according to the model $\mathcal{M}2.1$ for handling Example 2.

In the model $\mathcal{M}2.2$ (depicted by the right-hand scheme in Figure 7) there is no such loss of information, because D2 is appropriately modeled as a dynamic node. The effects of D1 in $t-1$

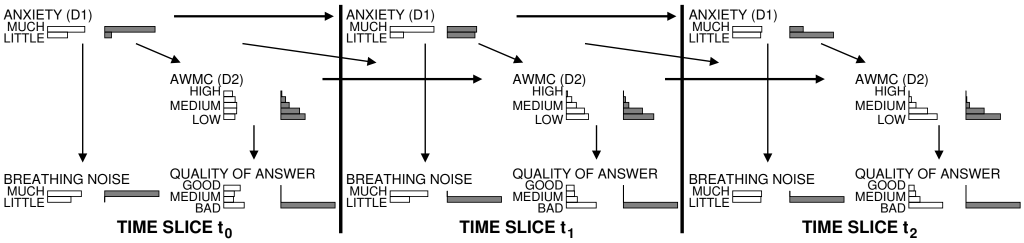

Figure 9. DBN according to the model $\mathcal{M}2.2$ for handling Example 2.

have been already considered in node D2 in $t-1$. Node D1 in t also incorporates the cause of these effects. It is important that the effects of D1 to D2 are not counted twice. Therefore, D2 in t is linked to D1 in $t-1$ and D1 in t. When defining the CPT for this dependency, D1 in both t and $t-1$ can be taken into account. Considering D1 in $t-1$ is important because D2 in $t-1$ was already influenced by D1 in $t-1$.

For example, in our domain we expect the AWMC in t to be roughly the same as that in $t-1$, if ANXIETY remains unchanged. If $\mathcal{P}$ calms down, we expect AWMC to increase and vice versa. In addition, if $\mathcal{P}$ is very anxious, we are more careful in ascribing a high AWMC to $\mathcal{P}$. In Figure 9 we show how Example 2 is handled by the model $\mathcal{M}2.2$. In this case no loss of information occurs; $\mathcal{P}$'s AWMC is estimated consistently as probably low. This seems more reasonable than the results obtained by the DBN modeled according to $\mathcal{M}2.1$.

Interpretation and prediction are more costly in $\mathcal{M}2.2$ than in $\mathcal{M}2.1$. In addition, $\mathcal{M}2.2$ is harder to model: The CPT for defining the dependency between D2 in t and its parents D1 in t, D1 in $t-1$, and D2 in $t-1$ necessary for $\mathcal{M}2.2$ requires more values than the CPT of the dependency between T and D1 for $\mathcal{M}2.1$. If we were interested only in estimating $\mathcal{P}$'s ANXIETY we would adopt Provan's (1993) proposal of trading accuracy against efficiency and prefer $\mathcal{M}2.1$. As can be seen in our example DBNs (see Figure 8 and Figure 9), there is nearly no difference in the estimate of $\mathcal{P}$'s ANXIETY. Our goal is to estimate $\mathcal{P}$'s AWMC; therefore we prefer $\mathcal{M}2.2$.

Dependencies between dynamic and static nodes. Sometimes a dynamic node D has a static parent node S, e.g., the parent node of AWMC (D) is INTOXICATION (S). Figure 10 depicts three schemes for modeling such a dependency. The models are illustrated using the following example:

> **Example 3:** The background noise of a call indicates that $\mathcal{P}$ is in a bar. The poor articulation suggests that $\mathcal{P}$ is drunk. Nevertheless, $\mathcal{P}$'s answers to three simple questions are all quite good.

For didactical reasons, in the following examples we do not take into account other causes for a reduction of AWMC than $\mathcal{P}$'s INTOXICATION. To make our figures smaller we use INTOXICATION as a root node. In the prior probabilities of INTOXICATION we consider that $\mathcal{P}$ is in a bar and therefore probably drunk.

Jensen (1995a) proposes the incorporation of the effects of the static node S in the dynamic child node D. In this way the dynamic node D represents all of the information and the resulting network is quite simple. This idea is adopted in the model $\mathcal{M}3.1$, which is depicted in the left-hand scheme of Figure 10. Problems arise because of two points:

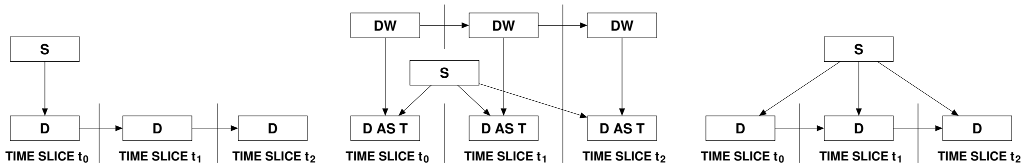

Figure 10. $\mathcal{M}3.1$ (left), $\mathcal{M}3.2$ (middle), $\mathcal{M}3.3$ (right): Modeling dependency between a dynamic node D and a static node S. Dynamic node DW in $\mathcal{M}3.2$ allows simplification of D as temporary node T (D AS T).

1. Node D must be able to represent the effects caused by S. For example, in Jensen's (1995a) wheat domain the effects of SOW DATE can be represented in the DEVELOPMENT STAGE. The DEVELOPMENT STAGE depends only on its predecessor in the previous time slice. In our domain this would not be proper, because $\mathcal{P}$'s AWMC in t depends on $\mathcal{P}$'s AWMC in $t-1$ and on $\mathcal{P}$'s INTOXICATION in t. If $\mathcal{P}$ is drunk, we will be more careful in ascribing a high AWMC to $\mathcal{P}$.

2. Often, static node S is initially not known with certainty; there is only a vague estimate. This estimate will be refined during the session, e.g., imagine that not until t_2 does it become clear whether $\mathcal{P}$ is drunk or not. There would be a problem if we had made a rollup in t_1: Nodes of time slice t_0 would be removed. The new evidence which refined the assessment of $\mathcal{P}$'s INTOXICATION can no longer influence AWMC in t_2 because these nodes are no longer linked. Without rollup, the network would grow until there were so many time slices (and nodes) that it would become intractable. However, this problem can be solved by trading accuracy for efficiency: Rollup has to be delayed until the influence of S on the current time slice becomes negligible.

In Figure 11 a DBN is depicted modeled according to $\mathcal{M}3.1$ dealing with Example 3. The result is questionable. Although $\mathcal{P}$ is assessed as drunk, $\mathcal{P}$'s AWMC is assumed to be medium up to slightly above medium (in t_3): Our network "forgot" (in t_1) that $\mathcal{P}$ is drunk and the (slightly below) good quality of $\mathcal{P}$'s answers is therefore interpreted too optimistically.

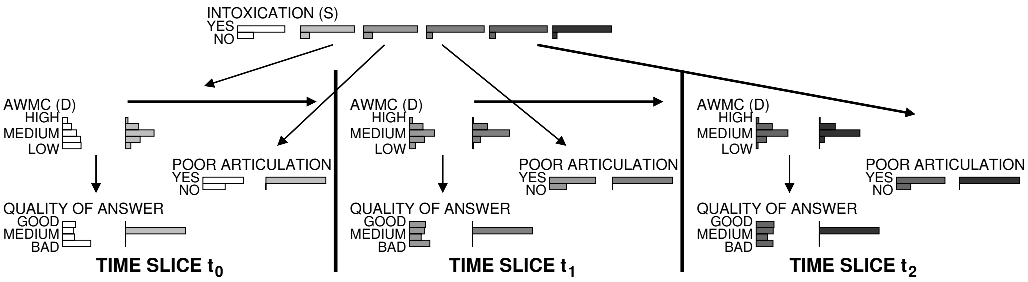

Figure 11. DBN according to the model $\mathcal{M}3.1$ for handling Example 3.

The model $\mathcal{M}3.2$ depicted in the middle of Figure 10 allows the static node to be refined during the session and to also have a direct impact on the estimate of $\mathcal{P}$'s AWMC in each time slice. In order to keep the model tractable, $\mathcal{M}3.2$ adopts Provan's (1993) proposal of trading accuracy for efficiency: D is represented as a temporary node T which will be created anew in each time slice (cf. $\mathcal{M}2.1$). DW represents the properties of D *without* the influence of S. T is created on the basis of DW and S. In our example AWMC (T) would be created in each time slice on the basis of INTOXICATION (S) and AWMC GIVEN SOBRIETY (DW). By applying rollup, the resulting DBN will be kept tractable.

Figure 12 shows the network modeled according to $\mathcal{M}3.2$ handling Example 3. We run into the same problem as with model $\mathcal{M}2.1$ (cf. Figure 8). Due to the process of recreating AWMC we have a loss of information. The belief of the recreated node AWMC in each time slice is less accurate than that obtained in the time slice before. This can be seen by comparing, e.g., the right-hand histogram of AWMC in time slice t_0 and the left-hand one in time slice t_1.

It is acceptable if the loss of information does not concern an important node. In our case, we are very interested in $\mathcal{P}$'s AWMC and therefore such a modeling is not acceptable.

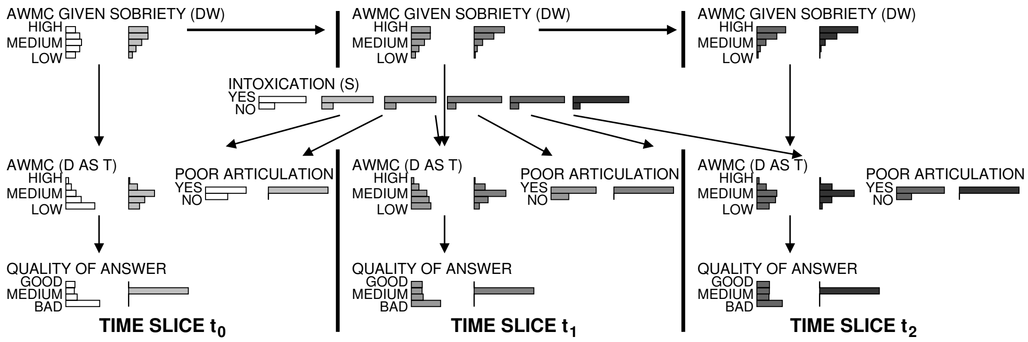

Figure 12. DBN according to the model $\mathcal{M}3.2$ for handling Example 3.

$\mathcal{M}3.3$ (cf. right-hand scheme in Figure 10) models S as static node and D as dynamic one. Such a structure is employed by Jensen (1995b) as a first model. Jensen (1995b) rejects this model for efficiency reasons.[9] In addition, his domain allows the use of the model $\mathcal{M}3.1$, which is unfortunately unsuitable for our purposes. Figure 13 depicts an example of how a DBN modeled according to $\mathcal{M}3.3$ adequately handles Example 3.

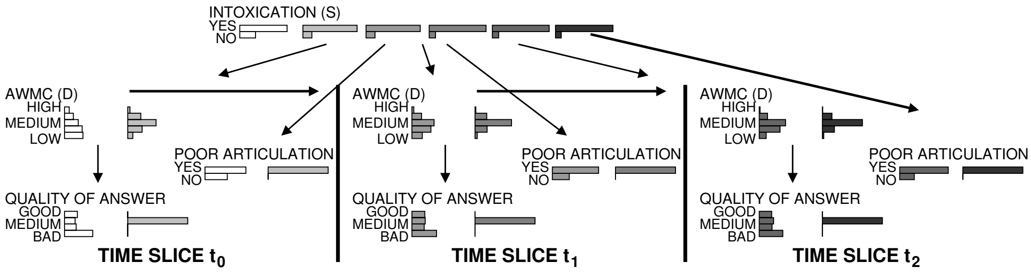

Figure 13. DBN according to the model $\mathcal{M}3.3$ for handling Example 3.

[9] There are nodes which are connected by two or more paths, i.e., the resulting network is multiply connected and requires costly inference algorithms.

In our examples, $\mathcal{M}3.2$ yields a similar result after the interpretation of the observable evidence of the rather good answers. If there were no such evidence $\mathcal{P}$'s AWMC would inadequately be assessed as low. This can be seen by comparison of the left-hand histograms of AWMC in time slice t_1 to time slice t_2. This is the reason why we prefer $\mathcal{M}3.3$ for modeling our domain.

For solving the problem of efficiency we again propose the trading of accuracy for efficiency. We therefore propose the use of rollups, but we delay their application so as to ensure that their effect is negligible.[10]

A variant of the model $\mathcal{M}3.3$ can be created by using the proposition made by Heckerman (1993). The static node is modeled as a dynamic one. The resulting model would be like $\mathcal{M}2.2$. This could perhaps be useful in simplifying the implementation: There would be no static nodes needing special handling when rollup is applied.

A theoretical possibility of a dynamic node as the parent of a static node still remains. That means that the proposition represented by the static node remains unchanged while its cause underlies continuous change. We doubt that there are examples of such dependencies.

4 Conclusions

In this paper we have characterized different types of dependencies that occur in networks that deal with the modeling of temporally variable user properties. We provided some general schemes which can be used to model these dependencies in a Bayesian network. The schemes were defined using existing techniques of applying dynamic probabilistic networks. We illustrated the proposed techniques with examples concerning emergency calls to the Saarbrücken fire department.

For the selection of a scheme, the dependencies among the variables of interest in the domain are the most important factors to consider. This is because the alternatives that we provided for keeping the networks tractable—by trading accuracy for efficiency—are not applicable in all domains.

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[10] A rollup is not trivial with a BN as defined by $\mathcal{M}3.3$. For reasons of space, we cannot explain the details.

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