Automatic Generation of Large Causal Bayesian Networks from User Oriented Models

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Abstract: Bayesian networks (BN) are a valid method to analyze causal dependencies with uncertainties and to calculate inferences based on evidences. This paper describes a method to enable domain experts to configure and use large causal Bayesian networks without the help of BN experts. For this the structure of the domain model is defined together with the domain expert. The dependencies of the domain model are weighted qualitatively. After that the domain model is translated into a well-defined BN. Within the BN the usual causal and diagnostic inferences can be calculated. The results are translated back into the domain model and presented to the user. The back translation also allows the presentation of the reasons of the inference results by using the causal dependencies of the BN. The translation processes allow translating user hypothesis by generating and calculating different BNs. As a benefit the method allows to generate and use large BN (with hundred of nodes) without excessive effort. Obviously in this approach probabilities are used in a special way. To motivate this, Bayesian probability concept is discussed before introducing the method. The method is illustrated by the example "Recognition of asymmetric or terroristic threats". At the end of the paper it is illustrated that the method can be used for different domains by a short description of the method's possible application to the domain "medical diagnosis". This paper does not deal with the theory of Bayesian Networks but with their efficient use.

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1 Introduction

1.1 The Bayesian Probability Concept

The Bayesian probability concept as used in this approach interprets a probability as "level of certainty in the assessment of an interesting fact." The theory and the algorithms of the probability theory are then used to successively reassess the facts by the user in the light of new findings or evidences. This approach allows to model a domain of reality with the help of probability theory and to use the powerful methods of the theory in cases where, strictly regarded, the elements of the reality are no statistic entities or processes. To use this probability concept it is necessary to model the facts in a way that their assessments fulfill the Kolmogorov axioms of probability theory [Kolm33] which reads in the form of assessment of facts as follows:

- Every assessment of a fact A(F) is described by a value between 0 and 1.
- Is a fact certain, this is modeled by A(F)=1.
- If there are mutual excluding facts $F_1,\ldots, F_n$, the assessment that any of the facts is true is equal to the sum of the singular facts: A(Any of $F_1,\ldots, F_n$) = $A(F_1) +\ldots+ A(F_n)$.

As the facts are regarded as probabilistic they are also random variables. Example: One may regard the color of cars as random variable. Then, the possible values of that variable are all possible colors of cars, and the probability that an arbitrary car is of a specific color can be determined. Obviously the axioms hold.

1.2 Bayesian Networks

In this chapter some fundamental definitions and results of the theory of BN are given. They follow [PNM08].

Definition: Conditional probability:

Let X_1 and X_2 be two random variables. Then the conditional probability of X_2 given the occurrence of X_1 is written as $P(X_2| X_1)$. In the color of car example, the probabilities of colors depend on car type. E.g., P(silver|Mercedes) might be 0.25 whereas P(silver|Ferrari) might be 0.001. In other words, the relation between type and color can be modeled as a cause-effect-relation where the type of the car is the cause and the color is the effect.

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Definition: Graph, directed, cyclic, acyclic

A graph is an abstract structure which describes a set of objects together with all connections between the objects. Formally it will be described by a tuple (V, E), where the set V (vertices) describes the objects and the set E (Edges) describe the connections. The vertices of a graph can be represented graphically by nodes or points and the edges by arcs.

If the connections have a direction, the edges can be represented by arrows and the graph is called **directed**.

A sequence $v_1, v_2, \ldots, v_l$, where v_i and v_{i+1} are connected for every $I \in (1,l-1)$ is called path. If the path contains at least two vertices which are identical it is called a cycle. A graph which contains at least one cycle is called cyclic, otherwise it is called acyclic.

Obviously the elements of a domain can be represented as the elements of V and the causal dependencies between the elements as the elements of E.

Definition: Bayesian Network

Let us consider n random variables $X_1, X_2, \ldots, X_n$. Suppose that the random variables X_i are associated to the vertices of a graph G. Define the arcs of the graph as follows: If there is a cause-effect-relation between the vertices X_i and X_j then there is an arrow between these nodes.

Then the graph is called a Bayesian network if the graph is acyclic.

As a consequence of these definitions a BN is a natural, intuitive and efficient way to model causal dependencies with uncertainties.

2 Problem Statement

For an efficient use of BN to solve real world problems it is necessary that the respective BN is applied by domain experts. Generally, operational experts have a good understanding of their subject domain matter. This includes *intuitive* statistical description of related facts [Krue 08]. In contrast, due to [GGI02], [GGE03] even well-educated humans have significant problems handling statistical information, *formally*.

In detail this includes i.e.:

- Domain experts often misunderstand conditional probabilities. Therefore it is hard for them to define the necessary tables of conditional probabilities.

- They also often have problems to interpret the calculation results. This is especially the case if a node of the BN is a multistate node where the average probability value is smaller than 0.5, because in this case a (relatively) "high" probability can be much smaller than 0.5.
- In several cases they might have problems to discriminate between the causes and the effects, which can lead to an improper defined causal structure of the BN.
- They may also have problems transferring their intuitive solution approaches (i.e. hypothesis building) into the adequate solution technique within BN theory.

A solution of these problems must have the following properties:

- The structure of the domain model must be defined in cooperation with a BN expert. Once defined the structure of the domain model must stay stable.
- The BN must preserve the causal structure of the domain model.
- The BN must be generated from the domain model automatically to enable the domain expert to configure the BN (indirectly) without help of BN experts.
- The results from the BN must be translated back into the domain model and presented in a user oriented way.
- The interaction of the domain expert within his model must be translated to the BN, the resulting solution must be translated back to the user model.

3 Generation of the Bayesian Network

The solution described in the following chapters has been developed for and is integrated in a demonstrator for automatic threat recognition built by IABG during a study called AUGE sponsored by German Bundeswehr Transformation Center [BSZ09]. The solution was developed in cooperation between IABG's experts in information fusion and domain experts. Computational linguists of the Fraunhofer Gesellschaft (FhG-FKIE) complemented the team to deal with the language input.

3.1 Definition of the Domain Model Structure

The domain model must contain the following elements:

- Elements of reality (factors) which define the possible results (facts) within the user's area of interest.
- Possible findings which change the assessment of the user concerning his interest (called 'indicators' in the following).
- Possible states or values of the factors and the findings.
- Causal dependencies between the factors. For these dependencies the associated semantic must be defined clearly and well understood.
- Knowledge about possible a priori weightings of different facts if applicable.

These properties are illustrated using the AUGE model. This model represents the view of domain experts concerning the relevant components of threats and their weighted dependencies. **Figure 1** shows the schema of the threat model of the AUGE system.

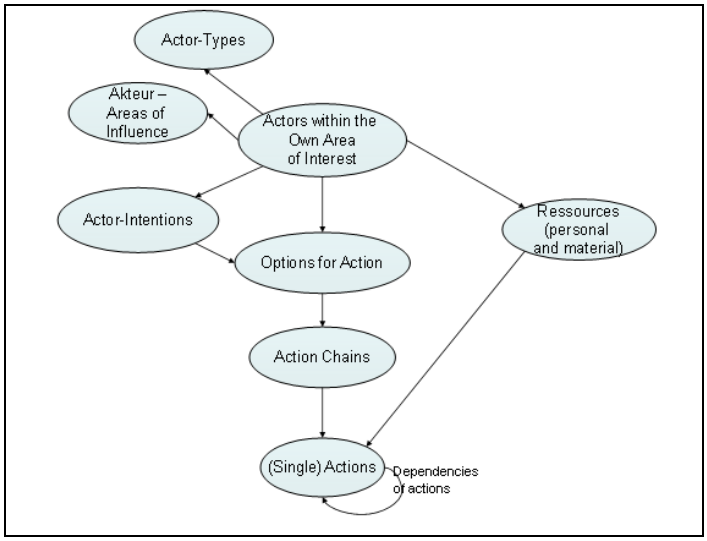

Figure 1: The threat model, its components and the dependencies among them

The factors of threats are as follows:

- Actors within the Own Area of Interest: organizations, groups or single actors which are regarded to be possibly threatening;
- Actor-Types: for example terroristic actors or actors from organized crime;
- Actor Area of Influence: areas in which a specific actor can perform actions;
- Actor-Intentions: for example “to destabilize the government of a country”;
- Options for Action: for example “to perform a bomb attack at a market place”;
- Action Chains: different specific approaches to convert a chosen option;
- (Single) Actions: the elements which constitutes an action chain;
- Dependencies of Actions: descriptions about which action has to be performed and successfully finished before another action can be started; i.e., a bomb has to be built before it can be deployed.

For every element of the threat model an indicator can be defined by the domain expert. The indicator models the domain expert’s know-how about possible observations or intelligence information which indicates that a defined model element is “true.”

3.2 User Oriented Configuration of the domain model

The main advantage of our approach is the possibility to configure and reconfigure the model for different applications by the user. E. g, the threat model can i.e. be configured to represent threats against missions of military forces or to represent internal threats against a country (i.e. by terrorists or organized crime).

The user oriented configuration consists of three parts:

1. The specific, possible states of the model must be defined. This task is easily carried out by a domain expert.
2. The possible findings and events which change the assessments (indicators) must be defined. This task is less easy because the definition of indicators often indirectly implies a description (or knowledge) by the domain expert on how to measure or how to observe the findings and events. In chapter 5, a short description is given how this had been done in the AUGE project.
3. The interrelations within the model should be weighted using a qualitative weighting schema like “very high”, “high”, “unknown”, “low” or “very low” according to ergonomics’ “scale based distribution retrieval” [Krue08].

The configuration process should of course be supported by a user oriented tool set. It is especially important to provide a user oriented visualization of the weightings to the domain expert. For example, in AUGE, actor “TALIBAN” (organization) has a “very high” intention to drive away the ISAF troops, but has a “very low” intention to get the Afghan government stabilized.

3.3 Translation of the Domain Model into a Bayesian Network

For preparation of the translation algorithm a BN expert must analyze which of the factors contain many mutual exclusive states and which factors contain states which can be truly parallelized. The factors with many states have to be modeled by multi-state nodes of the BN. The other factors have to be translated into multiple nodes of the BN by generating one binary node for every state of the defined factor.

With respect to indicators, it must be analyzed whether an indicator leads to binary results (true or false) only or whether it may provide results of uncertainty. In the latter case the method of so called soft evidences [AD09] must be used within the BN. It might also be analyzed whether an indicator contributes to the weighting in the BN even if the indicator does not match. If no match clearly indicates “the indicator is not true”, that indicator must be included. If no match, however, only implies “I don’t know because I have not observed it”, only the indicator with a match needs to be included.[1]

[1] Of course this is not necessary, but it can improve the performance of the calculation of the BN by reducing its size.

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The probability tables for the interrelations in the model are generated using the "scale based distribution retrieval". This approach comprises two steps. In the first step, the defined weighting values are transformed into scale values. The scale values are predefined values between 0 and 1 preserving the sequence which is given by the meaning of the qualitative values. In the second step, the resulting table column values are normalized as demanded by probability theory. The normalization step for dependencies of factors with many states leads to numerical values which are comparably small, even if the qualitative value of the dependency was "very high".[2]

The final step of the generation of the BN is the calculation of the probability tables of nodes which have more than one parent node. In these cases the domain expert should determine which parent has more or less influence on the dependent node. This information is to be translated as the scale based approach determines. After all the translations, the probability tables for multiple dependencies are calculated as usual.

Defined indicators serve as evidence nodes. Therefore, indicator matches are used for the diagnostic calculation. In our example, the structure of the BN had been generated from the threat model taking into account that a single threat can consist of multiple resources and multiple "single actions." Therefore the factor resources and the factor actions are translated in multiple binary nodes. For diagnostic calculation, only indicators with matches contribute to the BN and thus are included. The resulting BN structure is sketched in **Figure 2**:

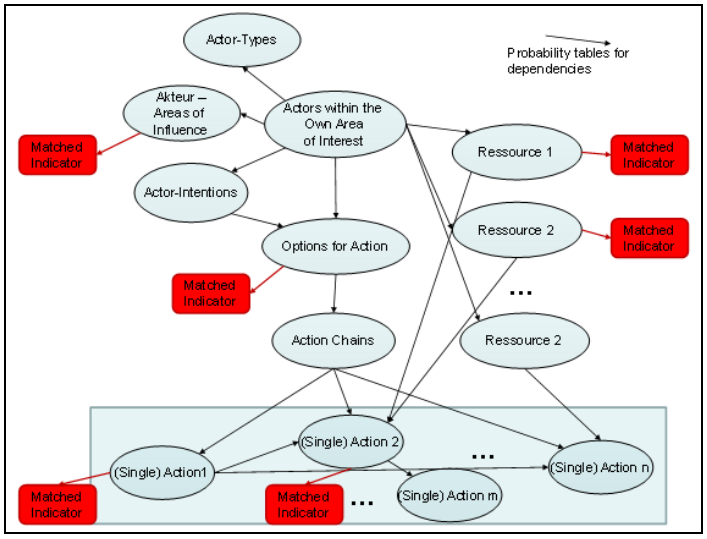


Figure 2: Bayesian Network

The next figures exemplarily show cut-outs of the resulting network and probability tables of the resulting network. The representations are taken from open-source software "ELVIRA" [ELV01].

[2] This should not irritate the BN expert but it would be puzzling for domain experts.

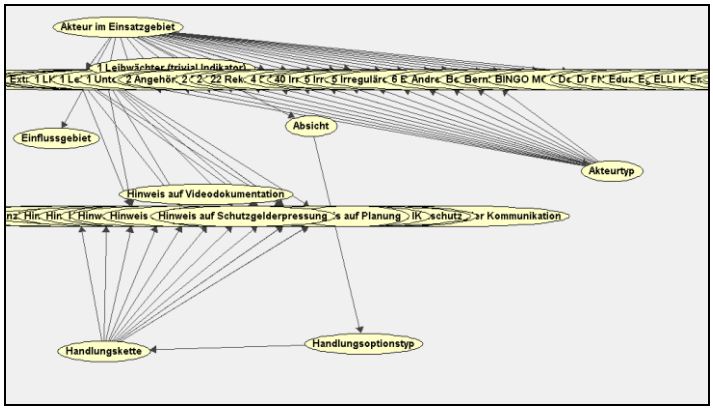
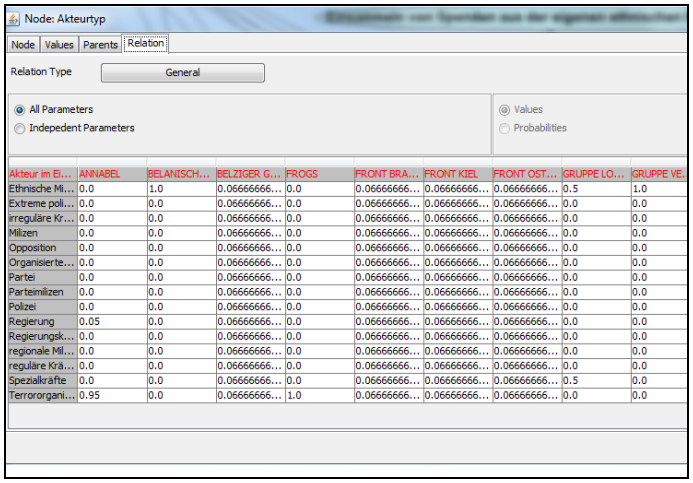


Figure 3: cut-out of automatically generated network



Akteur im Ei...	ANNABEL	BELANISCH...	BELZIGER G...	FROGS	FRONT BRA...	FRONT KIEL	FRONT OST...	GRUPPE LO...	GRUPPE VE...
Ethnische Mi...	0.0	1.0	0.06666666...	0.0	0.06666666...	0.06666666...	0.06666666...	0.5	1.0
Extreme poli...	0.0	0.0	0.06666666...	0.0	0.06666666...	0.06666666...	0.06666666...	0.0	0.0
irreguläre Kr...	0.0	0.0	0.06666666...	0.0	0.06666666...	0.06666666...	0.06666666...	0.0	0.0
Milizen	0.0	0.0	0.06666666...	0.0	0.06666666...	0.06666666...	0.06666666...	0.0	0.0
Opposition	0.0	0.0	0.06666666...	0.0	0.06666666...	0.06666666...	0.06666666...	0.0	0.0
Organisierte...	0.0	0.0	0.06666666...	0.0	0.06666666...	0.06666666...	0.06666666...	0.0	0.0
Partei	0.0	0.0	0.06666666...	0.0	0.06666666...	0.06666666...	0.06666666...	0.0	0.0
Parteimilizen	0.0	0.0	0.06666666...	0.0	0.06666666...	0.06666666...	0.06666666...	0.0	0.0
Polizei	0.0	0.0	0.06666666...	0.0	0.06666666...	0.06666666...	0.06666666...	0.0	0.0
Regierung	0.05	0.0	0.06666666...	0.0	0.06666666...	0.06666666...	0.06666666...	0.0	0.0
Regierungsk...	0.0	0.0	0.06666666...	0.0	0.06666666...	0.06666666...	0.06666666...	0.0	0.0
regionale Mil...	0.0	0.0	0.06666666...	0.0	0.06666666...	0.06666666...	0.06666666...	0.0	0.0
reguläre Krä...	0.0	0.0	0.06666666...	0.0	0.06666666...	0.06666666...	0.06666666...	0.0	0.0
Spezialkräfte	0.0	0.0	0.06666666...	0.0	0.06666666...	0.06666666...	0.06666666...	0.5	0.0
Terrororgani...	0.95	0.0	0.06666666...	1.0	0.06666666...	0.06666666...	0.06666666...	0.0	0.0

Figure 4: cut-out of probability table of a multistate node (actor->type)

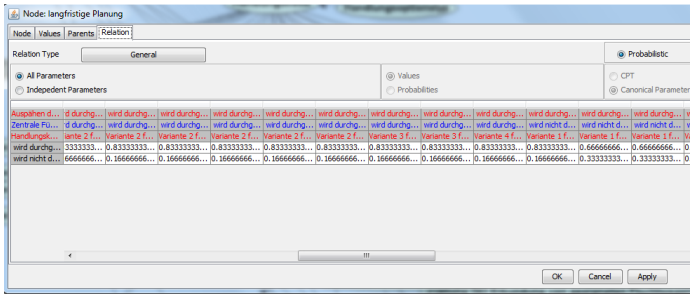


Figure 5: bi-static node with three parents

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In the cut-outs, one can easily notice which dependencies were defined by the user. In example the type of the "GRUPPE LOTHAR (GRUPPE LO… in the window) was defined as "Ethnische Minderheit" and "Spezialkräfte". In addition, it can also easily been noticed that the translation of the qualitative definitions weightings of the dependencies lead to probability tables with values corresponding to these values.

3.3 Back Translation of Calculated Results

When generated, the BN can be used to calculate inferences. The results have to be translated back to the user model by inverting the respective calculations.

4 Use of the resulting Bayesian Network

This chapter exemplarily describes how user interactions with the domain model are translated to the BN model. In general, it must mentioned that repetitive use of the model by domain experts requires (at least theoretically) the repetitive generation of the BN since it cannot be assumed that the situation has not changed. In particular, at least some additional indicator matches might have occurred which thus has to be included.

4.1. Causal Analysis

Doing a causal analysis the user will check the effects of the dependencies of the model if some states of the model are assumed to be true. In our example the user i.e. could pose the question "which actions must probably be expected if Al-QAIDA wants to destabilize the government?" This has to be translated as follows: Within the BN the according state values have to be set to 1.0 and the resulting a priori probabilities have to be recalculated. This leads to new values of the depending states including the values of the evidence nodes. This especially means that in using causal analysis the user can derive which indicators should be matched if some assumptions are made.

4.2 Diagnostic Analysis

For diagnostic analysis no further user interaction is necessary besides starting the calculation. After calculation, the Bayesian Network provides a result indicating threats on the verge. The result together with contributing evidences has to be presented to the user. Diagnostic analysis can also be run in batch mode. Then, the BN will be recalculated whenever there are significant changes in the evidence nodes, and warning messages are generated if the calculation results exceed predefined threshold values.

4.2 Analysis of Hypothesis

There are three types of hypothesis relevant in our applications:

- If the user makes a “hypothesis about the model” he assumes that some part of the model could be different. This only regards the possible states of the model, not its structure. In our example, the user might reason about possible new options for action, i.e. cyber attacks. The hypothesis formally just leads to a modification of the model and subsequently of the BN.
- If the user makes a “hypothesis about indicators” he assumes that at least one of the indicators is true although this is not confirmed by observation. This is formally modelled by setting the according evidence values to true (1.0).
- If the user makes a “hypothesis about facts” he assumes that a state of the model is true. In example he might assume that a specific actor is performing an action. In this case the associated state value in the BN has to be set to 1.0. After that the parent nodes of the regarded node have to be cut from the network.

In all cases the BN has to be recalculated.

5 Indicator Definition and Calculation

An important practical issue of the approach is to enable the user to define indicators in a user oriented way and in a way which can be used efficiently for the diagnostic analysis. To be able to prepare the possible indicators for a domain, an ontology of the domain can be used. The easiest usage of the ontology arises if the ontology models the indicators directly. This is the case i.e. in the medical diagnostics where all indicators for diseases can be modelled in an ontology using available classification schemas like the ICD–10 schema. In the diagnostic application the user (the doctor) can just manually declare the indicator matches using the predefined possibilities.

In the asymmetric threat examples it was necessary to enable the computer system to extract the information about indicators from unstructured text information. To support this, a verb based ontology was defined. This ontology provides information about the verbs in general and about their semantic frames in particular. Semantic frames are a further development of Fillmore’s case grammar [FIL68] that tells us which semantic roles come with the verb and which of these roles are mandatory, optional or forbidden. The frame of a verb mostly includes roles such as agent (the entity that executes the action), patient (the entity that is affected) and theme (the entity that is involved) but may also include spatial roles (i.e. location, direction) or temporal roles. A good semantic role set we largely follow is the one suggested by Sowa [SOW00].

Based on the verb ontology the user can construct specific indicators. For example, he can build an indicator for an IED attack. One possible trigger for that indicator is the procurement of an item used for IED construction. In order to define indicators and their triggers, we have developed an indicator editor that uses the verb ontology in the following way: In order to define an indicator by this editor, triggers have to be set up. To take the example, a possible trigger for the IED attack indicator is the procurement of large amounts of fertilizer for IED construction. In order to define that trigger, the procure entry of the verb ontology is marked as trigger action (central pane of the editor). As a consequence, the frame of that verb, *procure* in our case, is copied into the right pane which allows tightening of the match restrictions to what the role should be filled with. Here we can tighten our matching criteria so that the trigger fires only if certain persons (such as suspects) are recognized as agent of the procurement, if the theme is a certain sort of items or if the procurement takes place in a certain area and so on. In our case, we set the role *theme* to "fertilizer", so that the trigger only fires if somebody procures fertilizer but not if somebody procures i.e. humus (as it can not be used for IED construction), cf. **Figure 6.**

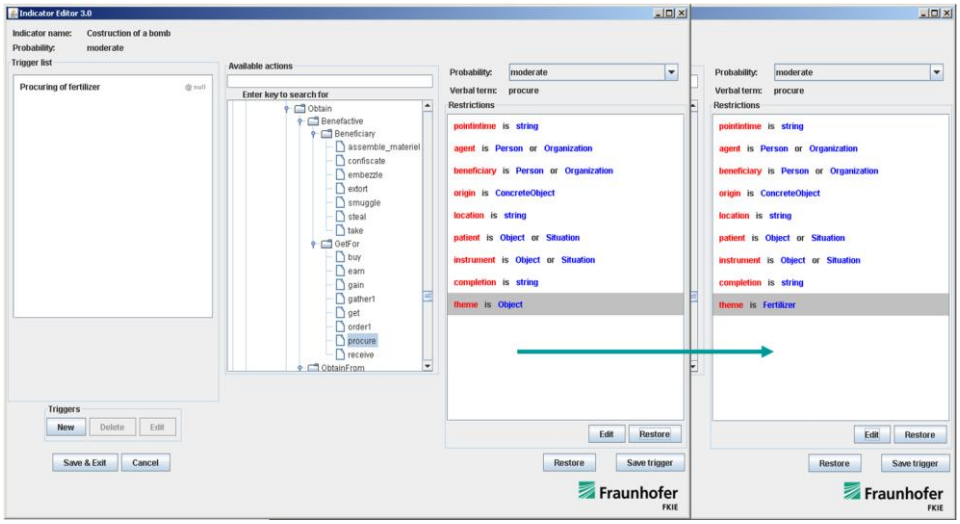

Figure 6: The indicator editor; defined trigger "procuring of fertilizer"

The indicators defined in this way form the basis for the use of an elaborated text mining approach called MIETER ("Military Information Extraction from texts and its Electronic Representation") [HSZ11].

6 Application of the Approach to Medical Diagnosis

In this chapter we show abbreviated how the approach can be applied to a different domain by presenting the domain user model and the structure of the resulting BN accordingly. The approach has been developed analysing a Bayesian network for liver disorders. The model covers 11 different liver diseases and 61 medical findings (indicators). The model is described in [AO08] and is available in the internet [GEN].

The generic domain model can be described as follows:

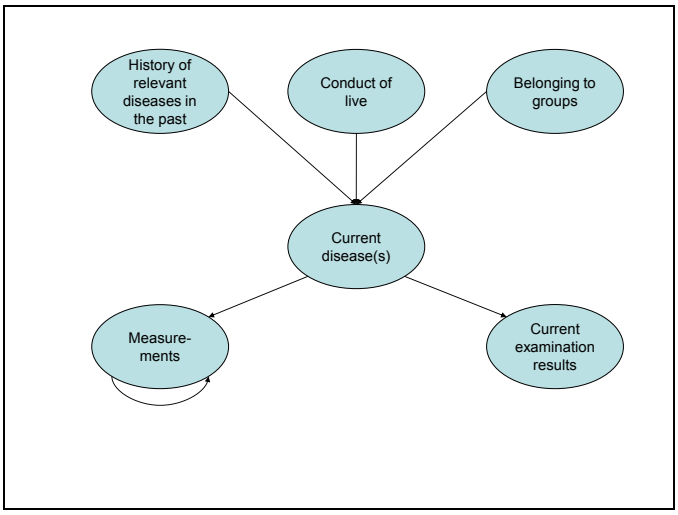

Figure 7: Medical diagnosis domain model.

For every specific area of diseases the domain expert now can define the relevant aspects of the domain:

- Which diseases in the past are relevant for the regarded diseases?
- Which "life style" factors (i.e. smoking, special sexual preferences, etc.) are important?
- Which group classifications (age, sex, etc.) are relevant?
- Which diseases are possible in the regarded area of interest? Which diseases can occur in parallel?
- Which measurements (blood, X-ray, etc) are indicators for a special disease? Which of them are dependent?
- Which results of the examination by the physician or the interview of the patient (respectively), i.e. (pain, etc.) are also indicators for a special disease?

The domain experts also have to qualitatively define the weight of the dependencies among the relevant factors. In this case every type of factor instance can occur in parallel to each other (i.e. age and sex). Therefore the generation of the BN for the domain model will lead to a network where the defined factors are distributed to different nodes.

Figure 8 shows a part of the BN as it is available in the internet [LINK !]:

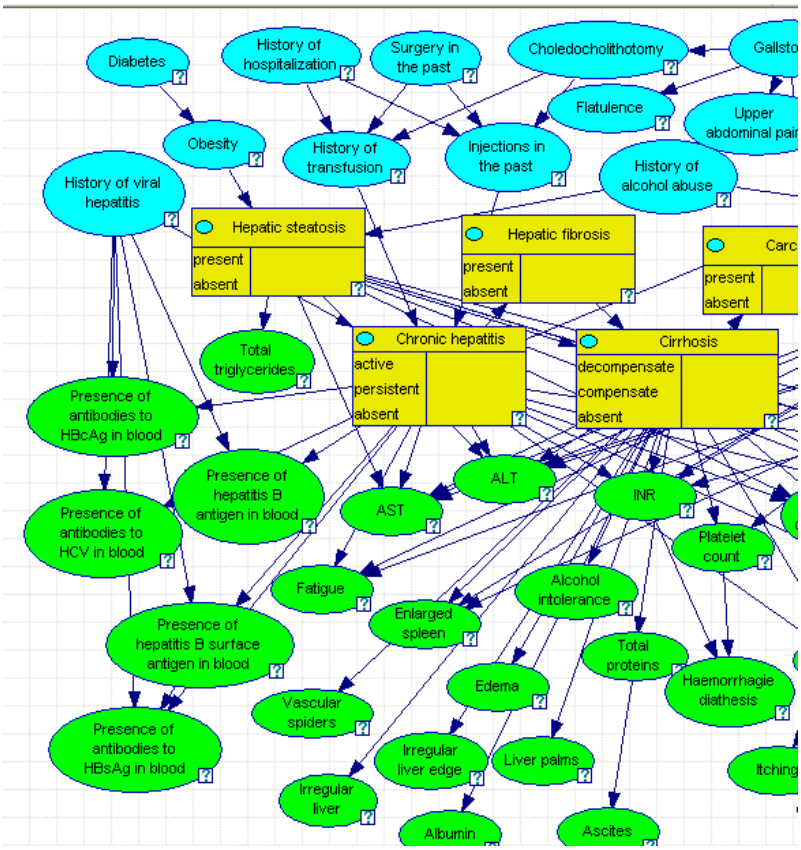

Figure: 8 Part of the HEPAR model

The blue nodes are the parents of the diseases; the green nodes are the measurements and the examination results. The yellow rectangles are the disease nodes.

7 Summary

The paper describes an approach to generate and use Bayesian networks by interacting with a domain model built and understood by domain experts. This approach clearly broadens the applicability of BN to areas where the direct use of the model by the users is not recommendable. The approach was developed for automated threat recognition. But it obviously can be used for additional applications, among them medical diagnosis.

8 References

[Kolm33] A. Kolmogorov. Grundbegriffe der Wahrscheinlichkeitsrechnung. Berlin, 1933.

[PNM08] Olivier Pourret, Patrick Naim, Bruce Marcot: Bayesian Networks. A Practical Guide to Applications. Chichester, UK: John Wiley and Sons, 2008.

[Krue08] Max Krüger, Jürgen Ziegler. User Oriented Bayesian Identification and its Configuration. Proceedings of the 11th international conference on information fusion, Cologne, Germany, 2008.

[BSZ09] Markus Bresinsky, Ulrich Schade, Jürgen Ziegler. Methodische Grundlagen zur Umsetzung des Konzepts "Automatische Gefahrenerkennung", Annex 2 of Final Report of the Study. 2009..

[HSZ11] Bastian Haarmann, Lukas Sikorski, Jürgen Ziegler. Applied Text Mining for Military Intelligence Necessities, *6th Future Security – Security Research Conference*, Berlin, 2011.

[ELV01] Homepage of ELVIRA Software: http://leo.ugr.es/elvira/

[GGE03] G. Gigerenzer and A. Edwards, "Simple tools for understanding risks: from innumeracy to insight," British Medical Journal (BMJ), 327, 7417, pp. 741–744, 2003.

[GGI02] Gerd Gigerenzer. Das Einmaleins der Skepsis. Über den richtigen Umgang mit Zahlen und Risiken. Berlin-Verlag, 2002.

[FIL68] Charles J. Fillmore. The Case for Case. In: Emmon Bach, Robert T. Harms (editors). Universals in Linguistic Theory. New York: Holt, Rinehart and Winston, 1968.

[SOW00] John F. Sowa. Knowledge Representation: Logical, Philosophical, and Computational Foundations. Pacific Grove: Brooks/Cole, 2000.

[AO08] Agieczka Onisko: Medical diagnosis example in [PNM08]

[GEN] http://genie.sis.pitt.edu/networks.html

[AD09] Adnan Darwiche. Modelling and reasoning with Bayesian Networks. Cambridge University Press 2009 (Chapter 3.6)