Medical Decision Support Tool from a Fuzzy-Rules Driven Bayesian Network

Vasilios Zarikas[1,2], Elpiniki Papageorgiou[1], Damira Pernebayeva[2] and Nurislam Tursynbek[2]
[1]*School of Engineering, University of Apllied Sciences at Central Greece (TEI of Central Greece), Lamia, Greece*
[2]*School of Engineering, Nazarbayev University, Astana, Kazakhstan*

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Abstract: The task of carrying out an effective and efficient decision on medical domain is a complex one, since a lot of uncertainty and vagueness is involved. Fuzzy logic and probabilistic methods for handling uncertain and imprecise data both provide an advance towards the goal of constructing an intelligent decision support system (DSS) for medical diagnosis and therapy. This work reports on a successfully developed DSS concerning pneumonia disease. A detailed and clear description of the reasoning behind the core decision making module of the DSS, is included, depicting the proposed methodological issues. The results have shown that the suggested methodology for constructing bayesian networks (BNs) from fuzzy rules gives a front-end decision about the severity of pulmonary infections, providing similar results to those obtained with physicians' intuition.

1 INTRODUCTION

Many techniques in the field of artificial intelligence have been used to represent knowledge: production rules, semantic nets, Bayesian nets, frameworks, scripts, statements, logic, causal networks, among others. Two significant topics of artificial intelligence are fuzzy logic and bayesian probability networks (Berner, 2007), (Konar and Chakraborty, 2005), (Konar, 2001). They have been shown to be effective in the medical decision tasks (Pearl, 2005), (Adlassnig, 1998), (Steimann and Adlassnig, 2000), (Chen et al. 2005), (Sittig et al., 2008), (Hudson, 2006), (Fox et al., 2010), (Charitos et al., 2009), (Fine et al. 1997). The choice of one of these two techniques is based on two main factors: the nature of the application and the designer's skills. Both decision making methods have been used in many applications in medicine.

In the last decade, probabilistic reasoning and fuzzy logic based methodologies were utilized in handling imprecise data in pulmonary infections (Pereira and Escuder, 1998), (Schurink et al., 2005), (Aronsky and Haug, 1999), (Hoare and Lim, 2006), (Saraoğlu and Sanli, 2007), (Cooper et al., 2005).

In this work, a useful step by step presentation of the design of an implemented DSS and its reasoning is given. It concerns pulmonary infections and a decision making concerning the severity of the disease (Zarikas et al., 2015). Physicians (stand as medical experts) reported certain and uncertain scientific knowledge concerning the disease of pneumonia (Mani, 2000). The physicians expressed their knowledge in the form of if-then rules. The designer of the network in cooperation with the experts/physicians assigned linguistic fuzzy values to describe the probability between the observables and the decision. Then these linguistic values were transferred to numerical values using defuzzification process in order to fill the conditional probability tables. Finally, the system forecasts the severity of pneumonia and drive a decision concerning their admission in Internal Care Unit (ICU). The simulations for test patients performed using the implementation of the proposed methodology.

The main objective of this paper is to introduce, analyze, and illustrate in a pedagogical way the methodology that have already been described mathematically in (Zarikas et al., 2015). Many researchers contacted us and required a more detailed description of the reasoning behind the formulas appeared in (Zarikas et al., 2015). Because of the relative novel character of the application in the field of medical sciences, this paper gives a detailed explanation on the proposed methodology and the application preview the effectiveness of the method.

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The paper is organized into the following sections: the second section presents a description on Bayesian networks and influence diagrams. It also provides a description on how fuzzy rules assigned by medical doctors, are used to construct conditional probability tables. The third section presents a statement of the problem and how the BNs for the specific problem is constructed by fuzzy rules introduction. The fourth section provides a description on stages of the development of the correct topology used in the BN tool, presenting the inference approach too. The fifth section outlines the results and the main conclusions of the study.

2 BAYESIAN NETWORKS AND FUZZY RULES

The definition of a consistent mathematical framework that allows the integration of certain and uncertain pieces of information into a plan of reasoning, would provide a necessary knowledge representation platform for every domain expert. Such a model of knowledge representation already exists and is known as belief network or Bayesian Network (BN) or causal graph (Jensen, 2000), (Pearl, 1988), (Stutz an Cheeseman, 1994), (Friedman and Goldszmidt, 1998), (Heckerman and Geiger, 1994).

Designing a Bayesian network means the following tasks (i) define arcs from cause variables to their effects; causal relationships reveal the conditional dependencies and independencies, (ii) assign values in Conditional Probability Tables (CPT) based on prior knowledge and data, (iii) finally appropriate algorithms have to been employed (Pearl, 1986), (Pearl, 1987), (Pearl and Verma, 1987) to determine various probabilities from the network.

The synthesis of Utility theory and Bayesian graph theory formulates the Decision theory (Winkler and Robert, 1972), (Horvitz, 1988), (Morgan and Bruce, 1968). The decision system that is described in the present work follows the usual assumptions. First we work with a set of mutual exclusive actions and non-intervening actions i,e, actions that their state is not correlated with P(H), where H is the determining variable that affects the decision. The expressive power of BNs becomes obvious considering that they can encapsulate statistical results, probability distributions, certain or uncertain opinions, utilities, preferences, strategies, goals and actions.

The fuzzy logic is based on fuzzy if-then rules which have the general form “IF X is A THEN Y is B,” where A and B are fuzzy sets. A fuzzy set is a set containing elements that have varying degrees of membership in the set. Elements in a fuzzy set, because their membership need not be complete, can also be members of other fuzzy set on the same universe.

The physicians express their knowledge in the form of fuzzy if-then rules due to the human thinking approach. The experts accompanied with the physicians assign linguistic fuzzy values produced by each IF-THEN rule, to describe the probability between the decision and the observables. These linguistic values, through the defuzzification approach of fuzzy logic, are transferred to numerical values in order to fill the conditional probability tables.

In order to show how the probability tables for BNs are developed using the above type of if-then rules, a generic approach is provided. Let’s consider the following rule for the assessment of risk or severity of an infection X: “IF symptom/observable-A increases Then severity of infection X decreases” (rule 1). This rule suggests information capable to provide probabilities for the conditional probability table (CPT) between the severity of infection and the observable A.

The above rule is translated as: there is a negative effect on severity from symptom A. This means that the lower state of severity conditioned on the higher state of symptom has a very very large probability. In the simple case that both ``symptom/observable A” and ``severity of infection/decision X” have only two states CPT assignment is shown in Table 1. The inference of the rule 1 could be described as:Rule Infer: The probability P(severity-|A+)=very very high. The linguistic description "very very high" might be assigned with a fuzzy set with corresponding membership functions.

Table 1: CPT of symbol A.

	Symptom A	
Severity X	+	-
+	complement	0.5
-	v.v. high	0.5

The membership functions that constitute the fuzzy sets which describe the inference of the fuzzy rules are depicted in Figure1. This means that from rule 1, there is a fuzzy belief which is assigned by the fuzzy set shown in Fig. 1. After defuzzification with the Center of Area method, a numerical value of each fuzzy set is produced. The produced numerical value is used to fill the probabilities in

CPT (Zarikas et al., 2015).

Therefore, we attempt to fill up the CPT for the different states of A and severity of infection X using this reasoning. In this point it worth stressing that experts together with the physicians assign the fuzzy values to describe the probabilities in CPT between the decision and symptoms. First, they extract the correct inference of the rule 1 i.e. that the probability P(severity-|A+) is "very very high". Second, the "very very high" probability is transferred to the numerical value of 0.9, according to the defuzzification process of the related fuzzy sets. If there is no information for the effect on severity X in the case that A decreases then neutral policy is followed. This means that a probability of 0.5 for both '+' and '–' states of a variable is assigned. This means that we assign probabilities following neutral policy. Thus, Table 2 changes to Table 3.

Table 2: CPT-probability (severity (X|A)).

	Symptom A	
Severity X	+	-
+	0.1	0.5
-	0.9	0.5

Let's consider the "opposite" case of a rule in the form: If symptom/observable A decreases Then the severity of infection X increases. Now the Infer of the rule is:

Probability P(severity+|A-)=v.very high and the CPT table is completed in an analogous way resulting to probability P(severity+|A-)=0.9. It is obvious that A is in general a different symptom than the one mentioned before in Tables 1, 2.

There are also cases that the number of states of the severity of a disease is more than two. In what follows, an explanation of how it is possible to construct CPTs for such multistate variables based on fuzzy rules is given. Let us work with the rule 1, "If severity A increases then severity of infection X decreases". Assuming that the symptom/observable A is described by three states: {weak, moderate, strong} and the severity or risk of infection X has four states: {small, medium, high and very high}, then for the CPT it is needed to assign values for: P(very small severity|A weak), P(very small severity|A strong), P(very small severity|A moderate), P(small severity|A weak), P(small severity|A strong), P(small severity|A moderate),....etc.

These probabilities are proposed to be described by eight (8) membership functions for P(severity_state$_i$ |A moderate) and P(severity_state$_i$ |A strong) borrowed from fuzzy logic methodology. Finally all P(severity_State$_i$ |A weak) are equal to 1/4 due to neutral assignment policy. These membership functions have been defined by the related fuzzy sets as illustrated in Figure 1.

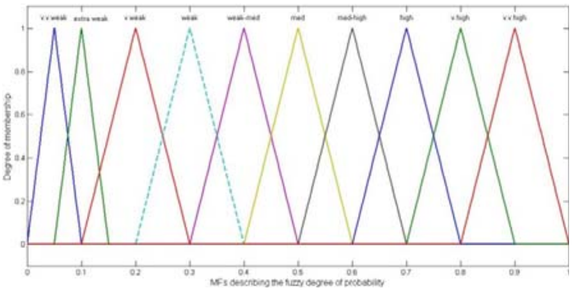

Figure 1: Membership functions used.

Thus the probability to decrease severity X as A increases could be assigned in a numerical value 0.7 derived by fuzzy sets as presented in membership functions describing the "high" probability. The following CPT for the different states of A and severity X is needed to fill up Table 3 considering the above fuzzy sets and their ranges.

Table 3: Probability (severity (X|A)) for multistate example.

	Symptom-A(state)		
Severity X	**Weak**	**Moderate**	**Strong**
small	-	medium high 0.6	High 0.7
med	-	weak 0.3	very weak 0.2
high	-	very weak 0.2	v.v.weak 0.1
very high	-	0	0

Next, Table 4 is filled up respecting axioms of bayesian probabilistic theory. Furthermore, neutral policy was also applied for the entries we have no information coming from the rule. It is worth mentioning that if a companion rule of the form "If symptom/observable A decreases Then the severity of infection X increases" then it would be possible to fill all the entries of the CPT.

Table 4: Probability (severity (X|A)) for multistate example.

	Symptom A		
Severity-X	Weak	moderate	strong
Small	0.25	0.55	0.7
Med	0.25	0.3	0.2
High	0.25	0.15	0.1
Very high	0.25	0	0

Let us now consider another type of medical rule with two observables A and B to determine the severity of an infection X. The severity of the infection X is considered to have four states: {small, medium, large, v.large}. The physician assigns next rule to determine severity:

``IF observable A is "Yes" and observable B decreases THEN severity of infection is medium". This rule could be infer the probabilities:

P(Severity med|low, Yes)=v.high (equals to 0.8)

P(Severity med|moderate, Yes)=high (equals to 0.7).

The CPT for the different states of observables A and B and severity of infection X is filled up as in Table 5.

Table 5: CPT-Probability (severity |AB,BA).

	(A)NO			(A)YES (exist)		
	(B) low	(B) mod	(B) high	(B) low	(B) mod	(B) high
Small						
Medium				0.8	0.7	
Large						
v. large						

Next step is to normalise the columns (A)YES-(B)low and (A)YES-(B)mod and finally complete all the other collumns following neutral policy. Thus, Table 6 (CPT-completed filled-Probability(Severity|B,A)) is derived.

Table 6: CPT-completed Probability (severity |B,A).

	Observable A					
Severity	NO			YES (exist)		
	low	mod	high	low	mod	high
Small	0.25	0.25	0.25	0.1	0.15	0.25
Medium	0.25	0.25	0.25	0.8	0.7	0.25
Large	0.25	0.25	0.25	0.1	0.15	0.25
v. large	0.25	0.25	0.25	0	0	0.25

3 PROBLEM AND TARGET

Some common criticisms about applied Bayesian networks concern the necessity of filling correctly a lot of conditional probability tables. However, the involvement of all these probability tables, is the reason that makes this decision tool extremely precise, expressive and mathematically consistent. BNs indicate emphatically to any decision builder how many pieces of information are involved for a precise decision making. The required big set of probabilities by no means can be disregarded unwisely for the sake of simplicity or approximation or a fault decision will be driven. However, it is possible to find methods for filling in a correct way the missing pieces of information. The present work describes such a method for the problem under study.

Another issue is that experts complain that the human brain does not work in this way and even scientists (not experienced in "Bayesian language") cannot easily report safely all these numbers in order to describe a domain knowledge. A practical solution of this problem is presented in this work for a particular medical case. However, the selected medical decision problem is not a special one but a quite typical and general case. Experts report a list of rules containing estimates about probabilities. These rules are a subset of all the possible rules that the full problem would require and the reasoning and the justification behind this reduction is explained in the relevant sections below.

For the chosen medical problem of pneumonia (pulmonary infections) the prediction of severity is a complicated process with many parameters, factors and preconditions (Gennis et al., 1989), (Langer 1994). See also CDC Criteria for Defining Nosocomial Pneumonia, online available in http://www.cdc.gov/.

For the problem of pneumonia, a number of typical symptoms are associated. If pneumonia is suspected on the basis of a patient's symptoms and findings from physical examination this indicates that more tests are needed to confirm the diagnosis. The set of all these data provide a basis for evaluation the severity of infection and the need for intensive care (Schurink et al., 2005).

Thus, severity of getting infected by pneumonia can be approximated by observing several symptoms. In the present work, three physicians (stated as experts), from the General Hospital of Lamia, Greece, were selected at first to define the number and type of symptoms-observables affecting the problem of pulmonary infection. Thirty-four different symptoms were reported, named from C1 to C34. These symptoms listed in Table 7, are well documented in bibliography. These are the main variables that have an important role in the final diagnostic inference. For this application, symptom/observable values take either two, three, four or five possible discrete or fuzzy values, as shown in Table 8. Each one variable/observable has different states, for example C4 (fever) is separated into five fuzzy values: no fever (36-38.4C), low grade (38.5-38.9C), moderate, high grade, hyperpyrexia (>41^{0}).

Next, the three physicians (expert doctors) were interviewed in order to construct a certain list of rules containing estimates of the probability of infection. Such rules, defining which symptoms increase or decrease the risk of infection, can build the base for a Bayesian network. The target is to encode the medical expert's knowledge about pneumonia in a Bayesian network. The complete set of rules can be found in the published work (Zarikas et al., 2015) in Appendix, "Rules". Rules have been given in the form of:

If Cn {increases|decreases|exists}then the risk of infection is {small|medium|large|very_large} or {increases, decreases},

while for two or more symptoms in the following form:

If Cn {increases|decreases|exists} and Cm {increases|decreases|exists}then the risk of infection is {small|medium|large|very_large}or {increases, decreases},

where Cn and Cm are two different symptoms. Experts have also stated that most of the times doctors know evidence for one, two or three at most symptoms from an examined patient.

Here it is worth pointing out that the proposed decision module is not a rule based expert subsystem. It is rather a probabilistic decision subsystem encoding medical "rules" expressing certain and uncertain knowledge. In order to design and implement the full Bayesian network with all the conditional probability tables a much larger set of rules is needed to cover them. However interviewing doctors, a medically correct strategy was constructed in order to fill the gaps in the probability tables.

So far, we have only presented a general approach on how from the previously mentioned fuzzy rules, CPTs are constructed. In what follows, the proposed approach as well as the overall reasoning is explored and analyzed to the particular problem to accomplish the final decision.

Table 7: Concepts coding pulmonary infections.

Nodes	
C1: Dyspnea	C17: Radiologic evidence of complicated pneumonia
C2: Cough	C18: Acidity (pH)
C3: Rigor/chills	C19: Partial pressure of oxygen
C4: Fever	C20: Partial pressure of CO2
C5: Loss of appetite	C21: Oxygen saturation O2%
C6: Debility	C22: White blood cells (WBC)
C7: Pleuritic pain	C23: Immunocompromise
C8: Heamoptysis	C24: Comorbidities
C9:Oxygen requirement	C25: Age
C10: Tachypnea	C26: Sputum culture
C11:Acoustic	C27: Bronchial secrets culture
character	
C12:(Glascow Comma Scale)	C28: Blood culture
C13:Systolic-Blood Pressure (mmHg)	C29:Pleural Fluid culture
C14: Diastolic bloolf	C30: Mantoux
C15:Tachycardia	C31:Gram stain (gram (+)
C16:Radiologic pneumonia	C32: Urinary antigen test C33: Pathogen Sensitivity

4 DESIGNING THE BAYESIAN NETWORK

In this section we describe how a Bayesian network is designed for the particular medical problem. We are going to create three types of nodes:

- for every symptom a symptom node
- for every rule or group of paired rules a rule node
- for every rule node a severity utility node
- one central utility comprising the overall utility and one decision node concerning admission to the ICU or not.

4.1 Symptoms

As a first step the symptoms should be entered in the BN, see Fig.2. In general, one symptom has different number of states according to physicians-expert knowledge and medical guidelines. Consequently, these states are associated with fuzzy membership functions, see Table 8 for examples.

Every symptom is represented by a probability informational node called Cn with the symptom's states as possible values for the node. From now on, these nodes will be denoted as symptom nodes.

The probability table of these nodes can be filled with certain or uncertain information (prior probabilities/evidences). Physicians report their knowledge by providing fuzzy rules based on their knowledge and guidelines from which our system extracts probabilities. This extraction is done following the method described in the section 3.

Table 8: Examples for symptoms.

Symptom	Type of values (discrete or fuzzy)
C7 Pleuritic pain	Two discrete values: 0, 1
C4 Fever	Six Fuzzy values ("hypothermia" (34-36), "no fever" (36-38.4), "low" (38.5-38.9), "moderate" (38.9-39.5), "high" (39.5-40.9), "hyperpyrexia" (>41))
C23: Immuno	Two fuzzy values (presence, absence)

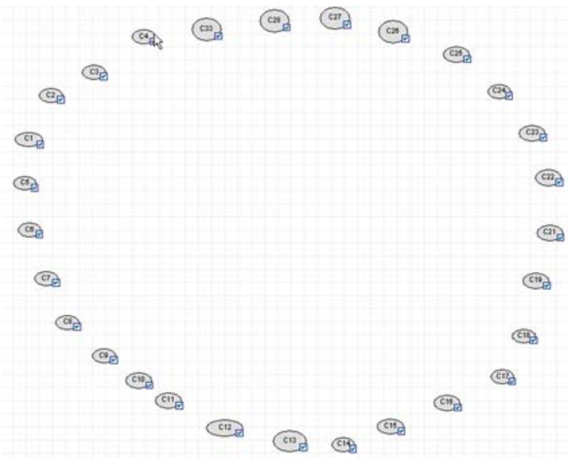

Figure 2: Symptom nodes.

Values according to the results of patient's examinations or according to physicians's subjective appraisal are entered. In case that there is no evidence for one particular symtom statistical data that can provide frequencies may be used either for the group that the patient belongs to, or for the patient's historic profile. Thus, for a particular case/patient the probability table for the symptom C7 Pleuritic pain could look like this opposed in Table 9.

Table 9: Probability table for the sympton C7 Pleuritic Plain.

C7 Pleuritic pain	Probability
State0	0.3
State1	0.7

Thus, the value 0.7 for the probability of State1 can arise from statistics about a high-risk group or from a doctor's judgment or patient's examination, see Table 9. In case a physician detects no clarity or definiteness on the answer of a patient he can assign a probability less than unity. If there is no evidence about the prior probabilities of a symptom node then a neutral policy regarding the prior probabilities can be applied (assign equal probabilities for a multiple state symptom). In most cases, soon after the patient's visit to the medical center only a few symptoms can be reported or measured with a certain or uncertain degree of belief. For the rest of them that remain unspecified, either a neutral policy should be followed in order to assign prior probabilities or (as in our case) the setup of an algorithm which disregards from the whole BN all the child of the non-relevant symptom nodes is needed.

4.2 Implementing the Rules

Medical rules encode the necessary information with the help of which, it is possible to associate probabilistically disease's severity and symptoms.

Table 10: Conditional probability table of the risk of infection node as a direct children.

Symptom 1	**State 0**									**…**
Symptom 2	**State 0**				**State 1**			**State 2**	**..**	**..**
Symptom 3	State 0	State 1	State 2	…	State 0	State 1	…	..	.	…
. .	. .	. .	. .	..	..	..	.	..	.	**…**
large severity	p1	p2	p3	…	…	…	…	..	.	…
small severity	1-p1	1-p2	1-p3	…	…	…	…	..	.	…

4.2.1 A First Topology

Naively, since all symptoms causally influence the node severity, a connection of all symptom nodes to the central node representing severity is expected. However, this design results to an non solvable topology. It generates a quite large probability table. Furthermore, for adding a new rule, it would be required to modify the values for the previous entered rules! In summary, a CPT that represents more than two or three rules is not manageable.

Table 10 illustrates clearly the complexity of the CPT in the simple case of a two-state severity node. The row large severity encapsulates the chances for large severity of infection, given the states of the column for the symptoms $(p_1, p_2, \ldots, p_m)$, where N is given by $N = \prod n_i$ with i=1,2,..k. where k is the number of symptoms and n_i the number of states of symptom i. The row small severity contains the complementary probabilities. It is obvious that although one rule concerns only one or two symptoms the topology results to the fact that every rule affects all probabilities in the CPT. Nevertheless, this is the correct topology that ideally represents the modelling of knowledge for the disease and its set of symptoms. This clearly shows all the elementary pieces of knowledge involved. Thus, in some cases, where a set of rules encode critical information, it may be necessary to acquire the relevant knowledge and construct a part of this very detailed topology.

4.2.2 Tractable Topology

A new simplified topology that works very efficiently is generated if for every rule a single rule node is assigned (see Figure 3). Fr this reason we name each rule node as *sev-Cn* or *sev-Cn-Cm* where n and m identify the symptoms involved in the rule. Rule nodes are causally affected by the symptom modes. In general, one or more symptoms affect one or more rules. Sometimes, it is preferable, two rules with the same symptoms to be combined in one rule node. Figure 3 shows the improved BN containing all symptoms and all rule nodes. Each rule node can be viewed now as a determining variable.

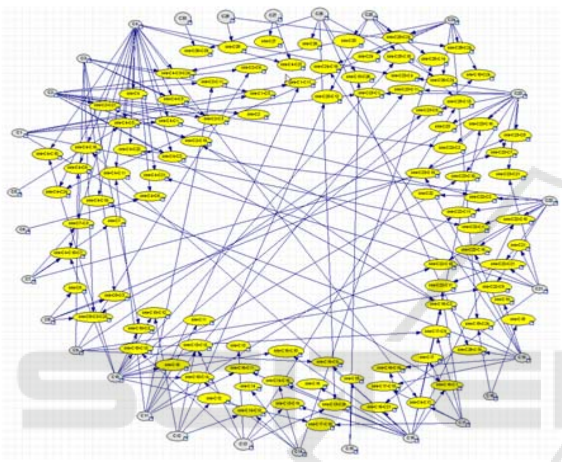

Figure 3: Rule nodes.

Although this is not a complicated topology many conditional probabilities have to be determined. Naively, one can say that the available rules provide less than the required amount of information. However, as we have previously explained physicians interpret and work with them in a way that allows to fill in the table. Let's explain the proposed method with one more example based on the following rule: “if symptom A is strongly in state1 (one of three states) then the severity of infection is large”. Apart from the obvious information that the conditional probability of large severity is a number close to unity conditioned on state 1, we can deduce more information. Following physicians' instructions, reported in the interviews, for some particular rules a complement (in our case small) probability for severity of infection can be assumed if the condition of the rule isn't satisfied.

However, note that for most cases the negation of the first part of the rule is connected with no preference i.e. leads to neutral assignment of probabilities for risk states. Such cases have already been presented in the previous section. Now what about the other states; if the states of the symptom A comprise an ordinal scale (state "1" is smaller than state "2" and state "2" smaller than state "3") then in most cases, except if physicians state otherwise, it is allowed to understand that the rule remains less true for symptom in state “2” and not true for symptom in state “3”.

Let's consider rule 30 and rule 31, see (Zarikas et al., 2015). These two rules can be represented by one combined rule node. When both these rules are not satisfied it means that they point to a not large severity. One can assign a conditional probability equal to 1 for C22 on state “normal” and on state “small” severity. Since the condition of the rule is not satisfied (C22 is neither in the higher state nor in the lower state) we assign 1 to the probability for a small risk independently of what is the state of C1. Alternatively another possible assignment is to set probability equal to one for P(severity|normal,state0) and P(risk|normal,state1) and a probability close to 1 (for example 0.9) for the other two P(severity|normal,state2) and P(severity|normal,state3) since the latter are associated with states of increased C1-dyspnea. Table 11 presents a first realization of rule 30 and its companion rule 31:

Table 11: Conditional probability table of the risk of infection node as a direct children.

C22	**leukopenia**	**Normal**				**Leukocytosis**
C1	**...**	**State 0**	**State 1**	**State 2**	**State 3**	**...**
small	...	1	1	0.8	0.8	...
medium	...	0	0	0.15	0.15	...
large	...	0	0	0.05	0.05	...
very large	...	0	0	0	0	...

Note that if in Table 11 all entries in the first raw (small severity) are set to one while all entries in all other rows (medium, large, very large) are set to zero, no large modifications will be raised in the final provision of decisions.

If C22 has the value leukocytosis means that C22 have increased and therefore the condition of the rule 30 is satisfied, provided that C1 is increasing too, pointing to large severity. Linear interpolation provides values in between, for the row “large”, see Table 12.

In case that C1 is in State1 or State2, P(medium|leukocytosis,1or2) is essential to be greater than 0. For example, it could be initially P(medium|leukocytosis,1or2)=0.3 and P(medium|leukocytosis,0or3)=0.

Table 12: First part of the probability table for rule C22-C1.

C22	Leukopenia	Normal	Leukocytosis			
C1	...	...	State 0	State 1	State 2	State 3
small	...	...	0.7	0.5	0.2	0
Medium	...	...	-	-	-	-
large	...	...	0.2	0.5	0.8	1
Very large	...	...	-	-	-	-

Next, row "large" is kept the same while reduced values of probabilities are set to the CPT entries above and below a specific element of row "large". Consequently, every column is normalized to a sum of 1 in each column. Therefore, following this reasoning, we retune values in Table 12, composing Table 13:

Table 13: First part of the CPT for rule C22-C1.

C22	Leukopenia	Normal	Leukocytosis			
C1	...	...	State 0	State 1	State 2	State 3
small	...	...	0.5	0.1	0	0
medium	...	...	0.15	0.2	0.1	0
large	...	...	0.2	0.5	0.8	1
Very large	...	...	0.15	0.2	0.1	0

Keeping the same reasoning (explained for leukocytosis), the column leukopenia can be determined by rule 31. The usage of all given riles resulted to the development of 102 rule nodes in the final decision network.

4.2.3 Connecting the Rule Nodes

After defining and setting all the rule nodes, the next step connects them with a utility node and through it to the final decision node. The Utility node can be modelled like Table14 and associates the decision node with the determining variable or variables. In this table a determining variable representing the total information which concerns the severity of the infection has been assumed. The decision node has been modeled with two states "Admission" meaning ICU admission and "No admission". Table 14 contains utility values for the four states of the determining variable. It will become apparent below that it is preferable to design more than one utility nodes (one utility for a group of similar determining variables). Now, determining variables are the so named rule nodes.

Table 14: First part of the CPT for rule C22-C1.

Determining variable of severity	ICU admission	no ICU admission
low	0	1000
medium	330	660
large	660	330
very_large	1000	0

The utility table is not a uniquely determined quantity. It reflects the strategy of the domain expert and thus different utility values can be set, depending on how conservative or strict is the selected policy. Physicians, suggest that a larger certainty for one state of severity of infection should be given, if more rules point towards it. However, in some cases that evidence is given (updating the prior probabilities of certain symptoms for a patient) a discrepancy may arise. If one or more rules indicate a small risk, while other rules indicate a large risk the implemented software provides a warning signal. This build in check of all active rules enhance significantly the performance of our decision tool. Note, that active rules are the rules that have been activated by updating the prior probabilities of certain symptoms.

4.2.4 Connecting All Rules

It was explained why it is not a wise choice to connect all the 102 rule nodes to one central utility node. The central utility node contains a double-row table with utility weights expressing the strength of infection for the given states of the parent nodes (Table 15). Therefore, a column represents one combination of states of the parents' nodes. Every rule node has four states small, medium, large and very large. So for every possible assignment of each of the 102 nodes with one of the 4 values, we need a utility table with 4^{102} columns, which are too many for a decision system to deal with.

However, for clarification reasons further elaboration on this topology with one utility will be devoted in order to illustrate the meaning of the entries of this utility table. The decision node ICU admission with the states yes and no allows defining utility values for these two states, see Figure 4 and Table 15.

A problem that appears usually in medical diagnostic decision systems is the possibility the reported symptoms to lead to a serious discrepancy regarding the risk/severity of infection. It is always possible a patient to report mistakenly a symptom that activate rule or rules that point to a very large risk/severity of infection while other symptom or symptoms point to small chance of infection. Therefore, a separate check for a discrepancy by an appropriate algorithm is necessary.

A significant remark is that in realistic cases only few rules from the whole set are activated by the updated symptoms. This has an important consequence. All these rule nodes that have not been activated by updated symptoms, are associated with a parent symptom node with neutral set of probabilities. This finally drives the system towards a neutral decision. If most rules are not activated and only two or three rules indicate with 0.8 chance a large severity, the final result through the utility node would point to a medium level expected utility value in the scale of 0-1000. This fact provides difficulties for the system to drive a clear positive infection decision. However, this is also an issue that can easily resolve with the help of a special algorithm that excludes non-activated rules.

The proposed solution includes an extra layer of utility nodes. Each rule node is connected to a utility node i-Cn-Cm which is named “admission node” (see figure 4). Thus, the role of the admission nodes is to convert the probabilistic representation of the severity of infection into a utility value as it can be seen in Table 15.

The central utility (weighted severity for admission) is the child of all admission nodes (see figure 4). This final node combines the utilities on admission from all rules together. Technically the central utility node is expressed by a utility node of type MAU (Multiple Algorithm Utility). MAU, utility node integrates many utility nodes with the help of a mathematical expression depending on the values of their parent nodes. It uses typical functions such as sum, division, maximum/minimum and logical operations.

Table 15: Theoretical Central Utility Table.

Rule 1	small	small	...	small
Rule 2	small	small	...	large
...	...	...	...	...
Rule n	small	small	...	medium
Infection	positive	negative	...	positive
Value	50	950	...	500
Rule 1	small	...	Very large	Very large
Rule 2	large	...	Very large	Very large
...	...	...	...	...
Rule n	medium	...	Very large	Very large
Infection	negative	...	positive	negative
Value	500	...	1000	0

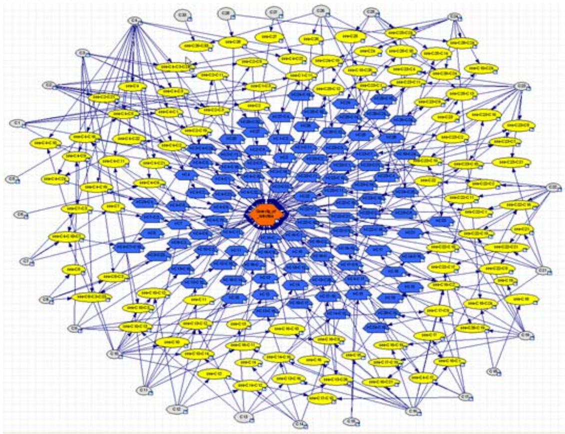

Figure 4: Inflection nodes (in blue).

The decision tool was developed based on the code of Bayes Fusion, given for academic use This software provides a built-in maximum function for MAU nodes. The code cannot support an estimation of the maximum over all rule values if they are more than 20. One solution is to collect the infection nodes into small groups and then calculate the maximum of the maximums. Another way is to assign equal weight to utilitiy of each rule.

In order to evaluate the severity of infection there is no need to take under consideration all the set of the rules. Since only a few symptoms are given for a particular patient, the rules that contain these symptoms will control the decision. Consequently, a few rules are often updated with non neutral prior probabilities which result in a noteworthy risk. However, as we have noticed the contribution of all the rest may affect considerably the final decision. This problem is resolved easier with the extra layer of utility nodes and the addition of a central node with a maximum MAU nodes evaluation scheme.

As a last step it's necessary to ensure that there are no discrepancies otherwise a notification has to be provided. As mentioned earlier we expect every symptom to report more or less the same results. If a patient has a very large and a small value of severity at the same time, something went wrong. The tool have implement an algorithm which evaluates the differences of the minimum and the maximum of all risks given by the selected rules. If the difference is above a predefined threshold the user is notified about.

5 RESULTS AND DISCUSSION

After construction of Bayesian network using the Bayes Fusion platform (https://www.

bayesfusion.com/), a number of patient cases have been examined in order to set evidences to the network and illustrate its decision-making capabilities. Specifically, (84) decision making cases on pneumonia severity assessment have been derived from a randomly selected set of anonymous patients with confirmed pneumonia. The decision-making capabilities of the technique was presented by simulating these patient cases and estimating the outcomes. The results have been reported in (Zarikas et al., 2015).

This work provides a pedagogical description of all the methodology that was followed to design the implemented DSS. It is a response to many requests to provide a clear explanation of the reasoning behind the formulas presented in (Zarikas et al., 2015). First, a new methodology for construction of BNs using if-then rules and main aspects of fuzzy logic is clearly presented and second, the efficient modeling and reasoning concerning the implementation of all rules to a network with a specific topology, is given. The method, we presented in this paper can be generalized to similar fuzzy rule bases.

Novel ideas that have been materialized in the DSS are: 1) Physicians have not been involved for the probability assignments but only for reporting and explaining the rules 2) Fuzzy rules have been translated into probabilities 2) There is an intermediate layer of utilities that transfer their values to a central utility node 4) The fuzzy rules are comprehensive enough for a physician, and describe a simple symptom/disease causal relation. A particular set of patients with pulmonary infections were studied as a first preliminary test of the decision making system on severity assessment and show the methodology's performance.

Future work is focused to analyze and implement this approach in other domains and decision problems, to include more knowledge and information types for the decision model enhancement. Specifically, extracted knowledge from other sources except physicians' suggestions, such as data through data mining and medical guidelines, will be taken under consideration for the model enhancement.

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