Fuzzy Knowledge Base for Medical Training

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Abstract. Currently, there are several approaches for representing medical knowledge and reasoning able to be interpreted by machines. They are the basis for applications like expert systems, clinical support systems, etc. The medical diagnostics context, on one hand, involves loosely delimited or intuitive characterization of some manifestations, on the other hand, the occurrence of manifestations and causal effects among them have grades of uncertainty. A representation approach that embraces both aspects is still an open challenge and it is the main problem addressed in this research. We propose here a model to represent medical knowledge for diagnosis, combining Fuzzy Logic, to express the loosely delimited concepts and probabilist networks. In this work, we are interested in the application of such knowledge base to support a medical training system.

Keywords: medical training,fuzzy logic, knowledge base, medical diagnosis

1 Introduction

The computerized healthcare support systems need approaches that reflect the medical reasoning. This is the reason why the knowledge representation has been getting a central role in some Medical Informatics. Over the last 20 years, several research groups have looked to find efficient ways of representing medical knowledge, as well as technologies and tools to support decision making and knowledge management [1, 2].

Previous investigations of Expert Systems provided the initial ideas for the current Knowledge-Based Clinical Decision Support Systems (CDSS). The goal was to build an expert system that could simulate human thinking [3]. Medicine is an area in which it is necessary to represent the human thought as realistic as possible, to easily withstand processes of patient care [2]. There are several ways of modeling medical knowledge. In this work, we will use the Markov Logic

Networks as a model base and an approach combined with Fuzzy Logic to model medical knowledge.

Consider the following example of a diagnostics statement:

`Hypotension can be related with arrhythmia in a patient.`

In order to model this statement to be interpreted and processed by a machine, we must consider three aspects, illustrated in Figure 1:

– Loose delimited concepts – hypotension is a concept derived from a low-pressure measure of a person; for very low values it is clearly identified, however, the boundaries for values near to the normal pressure are loosely defined.
– Uncertain causal relations – there is a probability of arrhythmia be related to hypotension.
– Network effect there is a network of interrelated manifestations, which also defines how arrhythmia will lead to hypotension and in what degree, as well as to other clinical consequences.

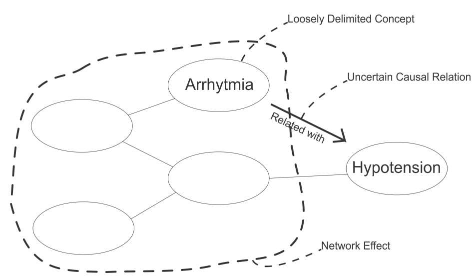

Fig. 1. Aspect of a diagnostic statement.

These three aspects were addressed by related work as follows:

Loose delimited concepts

Decisions of physicians vary according to their experience, skills, and perception. Decision on the same problem can vary from one physician to another and, therefore, it is necessary to deal with loose delimited and sometimes vague concepts, as in the case of hypotension. This problem can be treated by the fuzzy logic approach, which addresses also linguistic concepts of medical texts, as well as imprecision in knowledge [4].

The first expert systems enhanced the expression of if-then rules, using probability. Many of them evolved and still are being used. Zadeh [5] introduced a new theory to handle uncertainty. His theory of fuzzy sets also holds a theory of logic, fuzzy logic. The principle of this theory is that the objects of the world may belong in some degree to some set (degree of membership). For example, the set of tall people: a person p_1 who measures 1.85 is considered tall, but a person p_2 that measures 1.70 is considered to be almost tall. Then, we could say that person p_1 belongs to the set of tall persons in a degree of membership of 1, while the second person p_2 belongs to the set of tall persons in a degree of 0.7 [6].

Uncertain Causal Relations

The Markov Logic Network approach [7] maps first-order logic rules to Markov networks, which adds uncertainty to them, as probabilities of occurring. The Prade approach [8] associates probabilities to fuzzy logic rules.

Network Effect

The CASNET representation for expert systems establishes relations among observations, pathophysiological states and diseases as a causal network, which is the basis to support diagnostic decisions [9]. Barabasi et al. [10] extracted information from large-scale biomedical literature database (PubMed) to produce a network relating symptoms and diseases.

Combining the Aspects

As far as we know, related work addresses only part of these three aspects. Therefore, the main contribution of this work is the proposition of an approach that articulates the three mentioned aspects. This proposal focuses on the study and development of a medical knowledge base.

The remaining of the text is organized as follows: Section 1 presents the foundations and related work; Section 3 details our proposed approach to represent medical knowledge; Section 4 presents the conclusions and future work.

2 Foundations and Related Work

2.1 Fuzzy Sets and Fuzzy Logic

Most objects we can find in the real world can be categorized into well-defined sets (or classes). For example, the set of animals clearly includes: horses, birds, and lions. However, some individuals (objects) cannot be clearly classified within this class, such as bacteria. Another example is "the set of numbers much greater than 1" or "the set of beautiful women" or "the set of tall men". Thus, these types of sets or classes are called as fuzzy sets, where the elements or objects have a degree of membership with respect to them[6].

It is important to highlight that membership degree is not the same as probability. For example, in the definition of "drinkable" and "undrinkable", if the probability to take a cup of "drinkable" water is 0.7, this means that 7 of 10 water cups are drinkable and 3 are undrinkable. However, the idea of degree of membership comes when you conclude that, while there are cups of water clearly drinkable and others clearly undrinkable, there is a fuzzy frontier where a drinkable water starts to become undrinkable. The task is to judge a cup of water and give a membership value of "drinkable" water, for example, this cup has the value of 0.9 of "drinkable" water [11]. Using the membership function its define the basic operations in sets on Fuzzy Sets: intersection, union and complement.

In classical logic, the values of truth are true or false, in fuzzy logic, truth values follow fuzzy subsets of truth. For example, the variable age, which is defined by a range from 0 to 100, define several fuzzy sets that represent age, such as “very young”, “young”, “old”, etc. These fuzzy sets are linguistic variables.

2.2 Linguistic Variables

An intuitive way to see linguistic variables is to consider them as a “linguistic perspective” over values. Figure 2 shows the Age example, in which values of age ranging from 0 to 100 (bottom) are mapped to the linguistic terms: very young, young, old and very old (top). In simple terms. Linguistic variables are defined by linguistic terms, where each term is represented by a fuzzy set. In the example of ”Age”, its label is ”Age”, and its values are also be called ”Age”, with $U = [0, 100]$. Terms of this linguistic variable, called ”old”, ”young”, ”very old” and so on. The base-variable x is the age in years of life. $M(X)$ is the rule that assigns a meaning, that is, a fuzzy set, to the terms. The Figure 2 shows all linguistic terms of the variable ”age”.

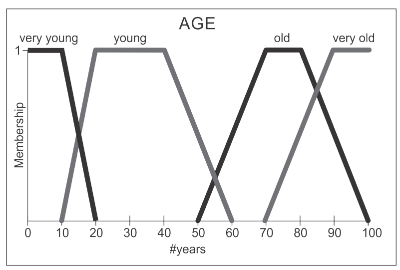

Fig. 2. Linguistic Variable ”Age” and its terms (fuzzy sets). (Derived from [12])

$T(Age) = \{$ very young, young, old, very old$\}$

2.3 Fuzzy Rule-Based Systems

A rule is a powerful mechanism to produce new knowledge departing from existing one. Let us consider the following statement:

If the diagnosis is Tachyarrhytmia with hypotension, the indicated treatment is Cardioversion.

This is a rule that produces a new knowledge (treatment) departing from an existing knowledge (diagnosis). Expressing it in a computational way, where disease and treatment are two variables:

```
IF disease IS Tachyarrhytmia and  bloodPressure IS hypotension
THEN treatment IS Cardioversion;
```

Fuzzy Rule-Based Systems (FRBS) born as an extension of Rule-Based Systems (RBS), but considering Fuzzy Sets and Fuzzy Logic to address uncertainty and the imprecision of human knowledge and reasoning. IF-THEN rules are composed of Fuzzy Logic statements. In a simple way, a FRBS is a tool to model different forms of knowledge, as well as the interaction between its variables [13].

On the one hand, we have the representation knowledge, which is basically linguistic variables, their respective linguistic values. On the other hand, we have reasoning mechanism [14]. The separation of the knowledge base and the processing structure is the main aspect to consider FBRSs as a type of knowledge base system [13].

2.4 Markov Logic Networks

Markov Logic Networks (MLN) are inspired by the need of a standard interface layer for Artificial Intelligence (AI), since in other sub-areas of computer science ,like database, this layer exists. The interface layer links the fundamentals, theories and/or infrastructure with existing applications or new application proposals in the different areas [7].

Going back to the *uncertain causal relations* mentioned in the Introduction and illustrated in Figure 1, the challenge is how to represent probable relations among elements. Consider the example illustrated in Figure 3, representing a chain of steps in a heart disease diagnosis. Each node is a pathophysiological state and the edges represent the probability of going to the next state, considering that a given state is achieved.

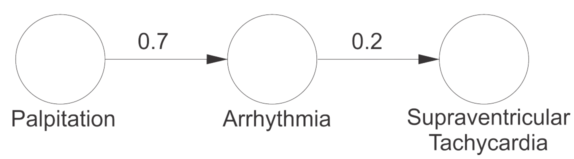

Fig. 3. Chain of steps in a heart disease diagnosis.

It is important to notice that the values in the example are merely illustrative and do not have any relation with real predictions.

This chain satisfies a Markov property if the predictions for the future – i.e., the probability for the next state – is based solely on its present state. This characteristic is sometimes called memorylessness.

Expanding this notion to a network, we can have a Markov Network, which is an undirected graph. The edges represent dependencies satisfying Markov properties of the random variables in the nodes.

Intuitively we can say that Markov logic is a language that combines first-order logic with Markov networks. The KB for Markov logic is a set of soft constraints on the set of possible worlds. When a world violates a formula, it becomes less likely, but not impossible, as in first-order logic. The weights of each rule can be interpreted as: the greater the weight, the more likely that the rule is true [7, 15].

2.5 Complex Networks

There are a lot of biological and social phenomena that can be modeled as networks, such as the complex network of chemical reactions that describe a cell; or the network of physical devices, like router, modems, and computers which define the Internet; another example is the network of companies and their exchanges of money and products among them, a business network; the network of researchers using citations to other researchers; the network of symptoms and diseases in humans. In this way, many more phenomena can be modeled as networks [16, 17, 10]

Therefore, approaches to address one type of problem can be reused in other types. For example, the PageRank algorithm [18] that Google used to rank pages on the Web network, have used for bibliometry and sociometry [19], and can be also used in the health context.

3 Fuzzy Knowledge Base for Medical Training

We further present our proposition combining these three aspects previously presented: loose delimited concepts (using fuzzy rules), uncertain causal relations and network effect.

3.1 Network modeling

The first challenge is how to model fuzzy rules and transform the uncertainty in the relationship between variables of these fuzzy rules as a Markov network. Our approach is inspired in the MLNs,the first step will be to associate weights to fuzzy rules, see Table1.

Table 1. Set of fuzzy rules

Fuzzy Rules	Weight
IF systolicPressure(x) IS low AND diastolicPressure(x) IS low, THEN bloodPressure(x) IS hypotension;	1.2
IF systolicPressure(x) IS normal AND diastolicPressure(x) IS normal, THEN bloodPressure IS normal;	1.3
IF systolicPressure(x) IS high AND diastolicPressure(x) IS high, THEN bloodPressure(x) IS high_normal;	1.8
IF systolicPressure(x) IS very_high AND diastolicPressure(x) IS very_high, THEN bloodPressure(x) IS hypertension;	1.6

The methodology to produce the network is still a work in progress, but Figures 4 and 5 shows two preliminary possibilities. The network shown in the Figure 4, each node represents a diffuse variable that contains its linguistic terms.

We could consider that each term is a node associated with the variable as shown in Figure 5. In this case, the relations will be among the terms instead of variables, i.e., systolicPressure(low) and diastolicPressure(low) are related with bloodPressure(hypotension). It should be noted that there are no similar proposals combining fuzzy logic with a network vision.

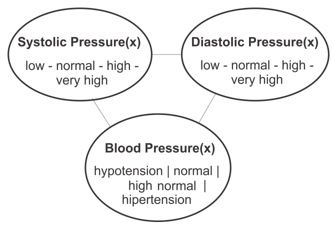

Fig. 4. Network of Fuzzy Variables

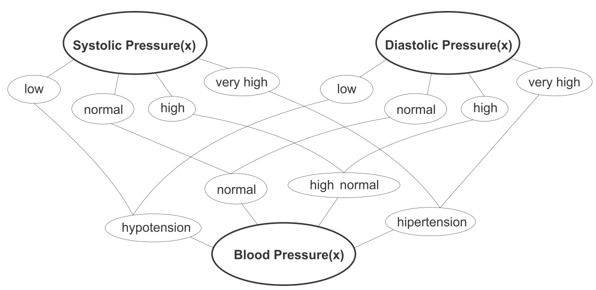

Fig. 5. Network of Fuzzy Variables and Terms

3.2 First-order logic and fuzzy logic

Although MLNs handle uncertainty by using weights in their formulas of first-order logics, they do not handle loosely delimited concepts. Therefore our proposal replaces first-order logic by fuzzy logic. It should be noted that not all variables must have fuzzy characteristics. Variables that have this behavior usually are those that have numerical values associated with them, such as blood pressure, age, height, heart rate, etc. Also some variables that denote graduation in linguistic form, for example, chest pain. Despite not possessing an associated numerical value, chest pain will be assigned to a range of numbers, for example [0,100] and its linguistic terms (without pain, low, normal,and high) can be divided into that range as follows:

```
FUZZIFY chestPain(x)
    TERM no:= (0, 1);
    TERM low := (0, 0) (10, 1) (40,1) (50,0);
    TERM normal := (40, 0) (50, 1) (80,1) (90,0);
    TERM high := (80, 0) (90,1) (100,1);
END_FUZZIFY
```

The fuzzy variable "Chest pain" is represented graphically in the Figure 6

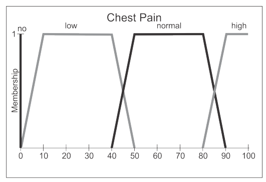

Fig. 6. Fuzzy Variable Chest Pain and his terms

Since our proposal works in a mixed way with diffuse and hard variables, it has to be able to handle sentences of the form:

```
IF oxygenSaturation(x) IS NOT normal AND bloodPressure(x) IS NOT normal
AND respiratoryRate(x) IS NOT normal
AND heartRate IS NOT normal AND faint(x)
AND (breathlessness(x) IS normal OR breathlessness(x) IS high)
AND palpitation(x) AND (chestPain(x) IS normal OR chestPain(x) IS high)
AND (dizziness(x) IS normal OR dizziness(x) IS high)
THEN arrhythmiaShock(x) IS very_likely;  1.6
```

In this sentence, the variables faint and palpitation are not fuzzy. Another advantage of having diffuse variables in our proposed model is that when programming an expert system, for the diffuse variables, we can have as input their associated numerical values, or their linguistic values to be selected, whereas with classical logic we only enter true or false. In the Figure 7 we can see how we can enter the value of the chest pain variable.

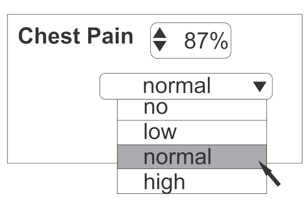

Fig. 7. Ways to select the input for the variable Chest pain

3.3 Learning structure, knowledge inference

The Alchemy framework for MLNs [7] provides a set of tools for learning the structure of its formulas in first-order logic. A challenge for our proposal is to adapt these algorithms to create the set of rules, where some variables are fuzzy.

The Alchemy framework also has the ability of querying, based on facts (basic nodes) to find the probability that a certain event occurs within the possible worlds. This feature will also be adapted to our proposal.

3.4 Complex Networks Vision

Another important aspect of our proposal is that we will try to verify if the diseases and symptoms network obtained by our model will have a complex network behavior, i.e., the characteristics of small world, scale-free topology among others. It will allow us to integrate with other works of disease networks. Relevant medical information can be found based on the topology of those networks.

By modeling the symptoms and diseases in the form of networks, we could obtain, for example, which disease (or diseases) have a greater measure of centrality (highest degree, PageRank, Betweenness centrality) within the network. Also, which are the most common symptoms among diseases. Through clustering algorithms, we can detect the diseases and symptoms that form communities among themselves. It is expected that the network of diseases obtained will be similar to those obtained in related work, this will also be a way of evaluating our proposal.

4 Conclusion

In this work, we propose an approach based on Markov Logic Networks [7], Fuzzy Logic [6, 20] and a topological vision of Complex Networks [21, 17], for modeling medical knowledge. It will be part of a bigger project and will serve as a basis for the creation of a game for Medical training.

In the first section fuzzy logic it is shown why this is a good choice for an approximation to human thinking (in our case medical thinking) since it is capable of using linguistic variables and treat reasoning with these variables. In the present proposal, we try to use the Fuzzy Logic to model the Knowledge Base, in a network model inspired by the Markov Logic Networks.

The next steps for the creation of this proposal is to create the model based on clinical data, for this we will test with different ways to infer diffuse rules for heart disease, based on works as Anooj [22], Khatibi [23] and more recent work as Animesh [24].

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