Fuzzy Knowledge Base for Medical Training

Ray Dueñas Jiménez[1] Roger Vieira Horvat[2], Marcelo Schweller[2],
Tiago de Araujo Guerra Grangeia[2], Marco Antonio de Carvalho Filho[2], and
André Santanchè[1]

[1] Institute of Computing University of Campinas (Unicamp)
{ray.jimenez, santanche}@ic.unicamp.br
[2] Emergency Medicine Department, Faculty of Medical Sciences
University of Campinas (Unicamp)
{roger.horvat.48, mschweller, tiagoguerra35, macarvalhofilho}@gmail.com

Abstract. There are several approaches for representing medical knowledge and reasoning, which are 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 – with probabilistic 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

Over the last 20 years, several research groups have looked for efficient ways of representing medical knowledge, as well as technologies and tools to support decision making and knowledge management. One key aspect is how to map the medical knowledge – which sometimes involves loosely delimited characterizations – to a machine interpretable format. Consider the following example of a diagnostics statement:

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

The goal of this research is to produce a model interpretable by machines to represent medical knowledge encompassing three complementary aspects, illustrated in Figure 1:

Loose delimited concepts: Decisions of physicians vary according to their experience, skills, and perception. A 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
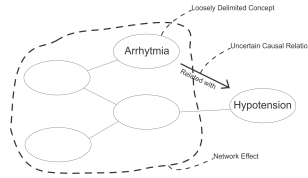
Fig. 1. Aspect of a diagnostic statement.

problem is treated in our model by the fuzzy logic approach, which addresses also linguistic concepts of medical texts, as well as imprecision in knowledge.

Uncertain Causal Relations:
Our model will be based on two other approaches. The Markov Logic Network approach [1], which maps first-order logic rules to Markov networks, adding uncertainty to them . The Prade approach [2] 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. Barabasi et al. [3] 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 propo- sition of an approach that articulates the three mentioned aspects. This proposal focuses on the study and development of a medical knowledge base. This project is part of a bigger project and will serve as a basis for the creation of a game for Medical training. The next step is to create the model based on clinical data. We will test different ways to infer fuzzy rules for heart disease, based on works as Anooj, Khatibi [4] and more recent work as Animesh [5].

The present work will support the production of clinical cases. The fuzzy logic, which uses rules with linguistic terms, facilitates the medical understanding of the models.

References

1. Domingos, P., Lowd, D.: Markov logic: An interface layer for artificial intelligence. Synthesis Lectures on Artificial Intelligence and Machine Learning **3**(1) (2009) 1–155
2. Prade, H., Richard, G., Serrurier, M.: Learning first order fuzzy logic rules. In: International Fuzzy Systems Association World Congress, Springer (2003) 702–709
3. Zhou, X., Menche, J., Barabási, A.L., Sharma, A.: Human symptoms–disease network. Nature communications **5** (2014)
4. Khatibi, V., Montazer, G.A.: A fuzzy-evidential hybrid inference engine for coronary heart disease risk assessment. Expert Systems with Applications **37**(12) (2010) 8536–8542
5. Paul, A.K., Shill, P.C., Rabin, M.R.I., Murase, K.: Adaptive weighted fuzzy rule-based system for the risk level assessment of heart disease. Applied Intelligence (2017) 1–18