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An Image Understandings by Fuzzy Logic

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Abstract—*This work relates to the development of computational algorithms to provide decision support to physicians. The authors propose a Fuzzy Naive Bayesian (FNB) model for medical diagnosis, which extends the Fuzzy Bayesian approach proposed by Okuda. A physician's interview based method is described to define a orthogonal fuzzy symptom information system, required to apply the model. For the purpose of elaboration and elicitation of characteristics, the algorithm is applied to a simple simulated dataset, and compared with conventional Naive Bayes (NB) approach.*

The case study on simulated dataset elucidates that FNB can be optimal over NB for diagnosing patients with imprecise-fuzzy information, on account of the following characteristics— 1) it can model the information that, values of some attributes are semantically closer than values of other attributes, and 2) it offers a mechanism to temper exaggerations in patient information. Although the algorithm requires precise training data, its utility for fuzzy training data is argued for. This is supported by the case study on infectious disease dataset, which indicates optimality of FNB over NB for the infectious disease domain. Further case studies on large datasets are required to establish utility of FNB.

1. INTRODUCTION

This work relates to the development of computational algorithms to provide decision support to physicians. Research on this problem was initiated five decades ago, with a probabilistic Bayesian model of physician's reasoning by Ledley and Lusted [1]. Ensuing pioneering work to develop and validate computer based decision support systems, used Naive Bayes (NB) [2], [3], followed by rule-based [4] and symbolic reasoning [5] approaches. In the last two decades, bayesian networks [6] and fuzzy set theory have been used to impart mathematical rigor to systems. For a historical review of Medical Decision Support research see Miller[7]. Later approaches include artificial neural networks [8], support vector machines [9], and information theory [10]. Overall Independence or Naive Bayes remains the most widely researched approach and many comparative studies have evaluated it as near optimal [11], [3], [12].

With the aim of improving the accuracy of diagnostic models, a soft computing approach using fuzzy relations [13], [14] was proposed by Sanchez [15]. Adlassnig [16] extended this approach and showed its utility with evaluative studies on Rheumatoid patients. Wagholikar and Deshpande in their recent case study [17] suggest a marginally improved accuracy of their alternative fuzzy relation based approach over Naive Bayes. Besides fuzzy relations, other fuzzy set theoretic concepts [18], [19] have been found useful for diagnosis.

In this manuscript we propose a Fuzzy Naive Bayesian (FNB) model for medical diagnosis, which extends the Fuzzy Bayesian approach proposed by Okuda [20]. A physician's interview based method is described to define an orthogonal fuzzy symptom information system, required to apply the model. For the purpose of elaboration and elicitation of characteristics, the algorithm is applied to a simple simulated dataset, and compared with conventional Naive Bayes (NB) approach.

2. PROPOSED METHOD

When there is uncertainty about the description of a particular symptom for a given patient, the information is fuzzy and the particular piece of symptom information is referred to as fuzzy symptom description or simply fuzzy symptom. In contrast crisp symptoms are those which are certain.

Each fuzzy symptom (indicated by underscore) is defined as a fuzzy set on the set of classical/crisp symptoms. The membership value of crisp symptom si in fuzzy symptom sk is obtained by interviewing physicians with the question "What is your degree of belief in sk when a patient asserts si"

For instance, fever can be described as absent (no), present (yes), or in terms of its grades–low and high.When symptom-descriptions are directly recorded from the patient, without an elaborate examination by the physician to establish the symptom, their values/grades are likely to be incorrect due to loose interpretations of the used vocabulary. The uncertainty resident in such information is vagueness or fuzziness [22], which is modeled by defining fuzzy sets for fuzzy descriptions of fever on the crisp descriptions of fever

Case study on simulated dataset

To elucidate the differences in FNB and NB approaches, we describe their application to a simple simulated dataset, limited to two diagnoses– Malaria and Tuberculosis and two symptoms– fever and cough. Assume that a training set having equal number of Malaria and Tuberculosis cases is obtained by an elaborate examination to establish the symptoms. The

Malaria patients have high-grade fever and no cough, which is typical for the disease [23], [24], and the Tuberculosis cases have the characteristic complaints of low-grade fever and cough [23], [24]. Since information in the training set has a high degree of precision, frequency counts on the training set will give accurate estimates for probabilities. Now we consider a test set comprised of cases which are not elaborately examined to establish their symptoms and the patient's narration is accepted verbatim. Such patient information is fuzzy, with some patients incorrectly grading their symptoms.

3. DISCUSSION

Results show that FNB correctly diagnoses the atypical case of Malaria, while NB is ambiguous as it computes equal scores for the diagnoses. Embodies the information that the modifiers low and high for fever are closer in meaning to each other as compared, to the modifiers no and yes for cough. This has an effect of decreasing the power of fever to discriminate between the diseases, where the difference in conditional probabilities of fuzzy symptoms- low fever and high fever is less than the difference for fuzzy symptoms- cough and no cough; while the differences are equal for their crisp counterparts.

Moreover captures the physician's belief that patients not having cough are more likely to report its presence, than the other way round. Hence, a complaint of cough should be more strongly interpreted as no cough than vice-versa. Similarly, patients having high grade fever are less likely to report it as low grade fever. It captures a widely held belief in the medical community, that patients often emphasize and exaggerate their problems [26], [27]. A consequence of modeling such information in FNB is that, the influence of higher gradations of symptoms, on the diagnostic computations is tempered, which filters out exaggerations in patient information. Demonstrates this effect of biasing the fuzzy symptom memberships towards lower symptom gradesthe membership value of crisp symptom-high fever in fuzzy symptom low fever.

4. CONCLUSION

The case study on simulated dataset elucidates that FNB can be optimal over NB for diagnosing patients with imprecise-fuzzy information, on account of the following characteristics—1) it can model the information that values of some attributes are semantically closer than values of other attributes, and 2) it offers a mechanism to temper exaggerations in patient information. Although the algorithm requires precise training data, its utility for fuzzy training data is argued for. This is supported by the case study on infectious disease dataset, which indicates optimality of FNB over NB for the infectious disease domain. Further studies on large datasets, are required to establish utility of FNB. The method may be particularly useful for inference from linguistic data, as such data is inherently fuzzy.

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