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IFS DECISION MAKING PROCESSES TO DIFFERENTIAL DIAGNOSIS OF HEADACHE

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Abstract

We are dealing with the preliminary diagnosis from the information of headache interview chart. We quantify the qualitative information based on the interview chart by dual scaling. Prototype of fuzzy diagnostic sets and the neural linear regression methods are estabilished with these quantified data. These new methods can be used to classify new patient's tone of diseases with certain degrees of belief and its concerned symptoms. We call these procedures as Neural Fuzzy Differential Diagnosis of Headache (NFDDH-1). Also we investigate three measures to medical diagnosis, where relations between symptoms and diseases are described by intutionistic fuzzy set (IFS) data. Two measures are deccribed by min-max and max-min IFS operators, respectively. Another measure is the similarity degree, i.e., IFS distance between patient's symptoms and prototypes of diseases. We consider some reasonable criteria for three measures in order to determine the label of headache. We will establish three measures in NFDDH-2 and combine two packages as NFDDH.

Key words. differential diagnosis, headache, IFS data, NFDDH

1. Introduction

In medical science the diagnosis can be regarded as a label assigned by the physician to describe and synthesize the medical status of a patient. It is based on the information about the patient collected by the physician and his present knowledge of medical sciences. He generally gathers the information , so-called symptoms, of the patient from the past history, the interview, the physical examination, laboratory results and other investigative procedures such as X-ray and ultrasonics. In the face of uncertainty concerning both the observed symptoms of the patient and the relations of the symptoms to a disease entity, the physician cannot avoid imprecision and uncertainty to determine the diagnostic label that will entail the appropriate therapeutic decision. Moreover, if the physician collects the qualitative information from the interview or the past history, the diagnosis is more complex and imprecise. Nevertheless, the physician is still quite capable of drawing conclusions from this information.

In this paper we are dealing with the preliminary diagnosis from the information of interview chart. The past history and the interview can be the most important tool in establishing the preliminary diagnosis for the patient. We quantify the information based on the interview chart by dual scaling and suggest how to establish the prototype of fuzzy diagnostic sets and how to classify new patients into one of diseases by the estimated neural linear regressions. Here we introduce two main relations between symptoms and diseases, and propose an inference method using Atanassov's IFSs. We use these methods to make twelve fuzzy differential diagnostic sets for headache [7,8]. We call these procedures as Neural Fuzzy Differential Diagnosis of Headache (NFDDH-1).

Here we introduce two main relations between symptoms and diseases, and propose three measures using Atanassov's IFSs. Two measures are deccribed by min-max and max-min IFS operators and another measure is the similarity degree, i.e., IFS distance between patient's symptoms and prototypes of diseases. We consider some reasonable

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criteria for three measures in order to determine the label of diseases. We will establish NFDDH-2 related to IFS measures.

2. Fuzzy inference methods in medical diagnosis

When evaluating the patient from the information of interview chart, the physician already determines different weighted values for multiple-choices compatible with each disease. After summing up the weighted values concerning with the patient in each of labels, he determines the label of a patient with the maximum value. In this classical diagnostic process some drawbacks are indicated : summing-up with independent relations between symptoms and personal weighted values for multiple-choices. The fuzzy set framework has been utilized in several different approaches to modeling the diagnostic process by Sanchez, Smets, Adlassnig, etc. Sanchez represents the physician's medical knowledge as a fuzzy relation between symptoms and diseases. Adlassnig elaborates on this relational model in the design of CADIAG-2, in which he proposed two types of relations between symptoms and diseases : an occurrence relation and a confirmability relation [2,9]. We propose an inference method using Atnassov's IFSs.

2.1 Fuzzy prototypes for physician's knowledge and experience

We apply Nishisato's dual scaling method to the qualitative information, and prototypes of fuzzy differential diagnostic sets are obtained by the medical knowledge and fuzzy neural linear regressions for non-fuzzy data.Suppose that each of n patients checks the interview chart with m multiple-choices and data matrix $F_{n\times m}$ is classified typically into diagnostic labels by the physician's knowledge and experience [6,15,17]. We can determine the vector $Y_{n\times 1}$ and $X_{m\times 1}$ by dual scaling, which is based on two principles of internal consistency and constant proportionality[16]. Each component of a vector Y is corresponding to a wieghted value of a patient and a vector Y is divided into clusters, i.e., labels as already indicated by data matrix F, with approximately one degree of membership and a vector X corresponds to weighted values of multiple-choices. Y can be explained by some components of X and the estimated Y can be inferred by linear combination of components of X. We can determine fuzzy trapezoidal numbers, fuzzy labels of diseases, by the medical knowledge and fuzzy neural linear regressions. In addition to them we can find symptoms which are essentially related to the label of disease [6,7,15,16].

2.2. Neural inference procedure

We adopt neural inference procedure to estimate weighted values of a new patient and represent the relationship between the patient and his symptoms by the model of neural linear regression. The model of neural linear regressions for classifying the diseases is defined as the following:

$$Y_j = a_0 + \sum_{i=1}^{m} a_i X_{ij}$$

X_{ij} is interrelated with the value of i-th symptom of j-th patient. Y_j is the value of weight of j-th patient.

The following energy(objective) function is proposed for the inference.

$$\min Energy_{Fcn} = \sum_{j=1}^{n}[\, Y_j - (a_0 + \sum_{i=1}^{m} a_i X_{ij})]^2$$

Our energy function is that of choosing a_i which requires to minimize above energy function.

We applied the new parallel mean field annealing algorithm to neural inference procedure. The used algorithm is below;

STEP 1: Initialize all neurons to the averages and the values of temperature T

STEP 2: Loop until a fixed point is found:

(1) Select a neuron a_i at random

(2) Perturb output value

(3) Calculate the energy function $\Delta E = E_{new} - E_{old}$

(4) If $\Delta E <= 0$, accept with Probability(accept)=1

Else accept with Probability(accept)=exp($-\Delta E/T$)

(5) Compute mean field E_a :

The average of output values of accept neurons

STEP 3: If T reaches the final temperature, then Stop

Else decrease the temperature

Go to step 2

Details of the above algorithm can be found in Yu and Lee [12].

3. Occurrence and confirmability relations based on IFS data

An IFS A in a fixed set E is an object having the form $A = \{\langle x, \mu_A(x), \nu_A(x)\rangle | x\in E\}$, where the functions $\mu_A : E \to [0,1]$ and $\nu_A : E \to [0,1]$ define the degree of membership and the degree of nonmembership of the element $x\in E$ to the set A, respectively, and for every $x\in E : 0 \le \mu_A(x) + \nu_A(x) \le 1$.

$\overline{A} = \{\langle x, \nu_A(x), \mu_A(x)\rangle \mid x\in E\}$ is defined as the complement of an IFS A. Obviously, every fuzzy set has the form $A = \{\langle x, \mu_A(x), 1-\mu_A(x)\rangle \mid x\in E\}$.

3.1 Max-Min relation based on IFSs

Let S = { $S_1, ..., S_m$ } be the set of symptoms, D = { $D_1, ..., D_n$ } the set of diseases and P = { $p_1, ..., p_a$ } the set of patients under consideration.

In Adlassnig's paper[2], he introduced the inference method for CADIAG-2, which incorporates relations not only between symptoms and diseases but also other combinations of them. There are two main aspects of a symptom S_i in order to find out its relation to a disease D_j;

(1) Occurrence of S_i in case of D_j : "How often does S_i occur with D_j ?"

(2) Confirmability of S_i for D_j : "How strongly does S_i confirm D_j ?"

Let us define an intuitionistic fuzzy relation R_S on the set P × S where membership grade $\mu_{R_S}(p, s)$ indicates the degree to which the symptom s is present in patient p,

$R_S = \{\langle (p, s), \mu_{R_S}(p, s), \nu_{R_S}(p, s)\rangle \mid (p, s) \in P \times S\}$.

$\mu_{R_0}(s, d)$ indicates the frequency of occurrence of symptom s with disease d and $\mu_{R_C}(s, d)$ corresponds to the degree to which symptom s confirms the presence of disease d. Four different intuitionistic fuzzy indications are calculated by means of intutionistic fuzzy relation compositions :

1. S_iD_j occurrence indication $R_1 = R_S * R_0$

$$\mu_{R_1}(p, D_j) = \underset{S_i}{MAX\,MIN}\{\ \mu_{R_S}(p, S_i)\ ;\ \mu_{R_0}(S_i, D_j)\} \quad (3.1)$$
$$\nu_{R_1}(p, D_j) = \underset{S_i}{MIN\,MAX}\{\ \nu_{R_S}(p, S_i)\ ;\ \nu_{R_0}(S_i, D_j)\}$$

2. S_iD_j confirmability indication $R_2 = R_S * R_C$

$$\mu_{R_2}(p, D_j) = \underset{S_i}{MAX\,MIN}\{\ \mu_{R_S}(p, S_i)\ ;\ \mu_{R_C}(S_i, D_j)\}(3.2)$$
$$\nu_{R_2}(p, D_j) = \underset{S_i}{MIN\,MAX}\{\ \nu_{R_S}(p, S_i)\ ;\ \nu_{R_C}(S_i, D_j)\}$$

3. S_iD_j non-occurrence indication

$R_3 = R_S * (1 - R_0)$

$$\mu_{R_3}(p, D_j) = \underset{S_i}{MAX\,MIN}\{\ \mu_{R_S}(p, S_i)\ ;\ \nu_{R_0}(S_i, D_j)\} \quad (3.3)$$
$$\nu_{R_3}(p, D_j) = \underset{S_i}{MIN\,MAX}\{\ \nu_{R_S}(p, S_i)\ ;\ \mu_{R_0}(S_i, D_j)\}$$

4. S_iD_j non-symptom indication

$R_4 = (1 - R_S) * R_0$

$$\mu_{R_4}(p, D_j) = \underset{S_i}{MAX\,MIN}\{\ \nu_{R_S}(p, S_i)\ ;\ \mu_{R_0}(S_i, D_j)\} \quad (3.4)$$
$$\nu_{R_4}(p, D_j) = \underset{S_i}{MIN\,MAX}\{\ \mu_{R_S}(p, S_i)\ ;\ \nu_{R_0}(S_i, D_j)\}$$

Finally, we may include in our set of diagnostic labels for patient p any disease d such that both inequalities 0.5<max[$\mu_{R_1}(p, d)$, $\mu_{R_2}(p, d)$] and max[$\nu_{R_1}(p, d)$, $\nu_{R_2}(p, d)$] <0.5 are satisfied [2].

3.2 Min-Max relation based on IFSs

Let us consider an IFS $R = \{\langle s, \mu_R(s, d), \nu_R(s, d)\rangle | s \in S\}$, where $\mu_R(s, d)$ corresponds to the degree that symptom s confirms the presence of disease d and $\nu_R(s, d)$ to the degree that confirms no presence of disease d and $1 - \mu_R(s, d) - \nu_R(s, d)$ to the degree of indeterminancy of disease d, denoted by *Rnond*.

5. S_iD_j confirmability indication $R_5 = R_S \circledast R_c$

$$\mu_{R_5}(p, D_j) = \underset{S_i}{MIN\,MAX}\{\ \mu_{R_S}(p, S_i);\ \mu_{R_c}(S_i, D_j)\} \quad (3.5)$$
$$\nu_{R_5}(p, D_j) = \underset{S_i}{MAX\,MIN}\{\nu_{R_S}(p, S_i);\ \nu_{R_c}(S_i, D_j)\}$$

6. S_iD_j disconfirmability indication

$R_6 = R_S \bullet (1 - R_c)$

$$\mu_{R_6}(p, D_j) = \underset{S_i}{MIN\,MAX}\{\ \mu_{R_S}(p, S_i);\ \nu_{R_c}(S_i, D_j)\} \quad (3.6)$$
$$\nu_{R_6}(p, D_j) = \underset{S_i}{MAX\,MIN}\{\nu_{R_S}(p, S_i);\ \mu_{R_c}(S_i, D_j)\}$$

7. S_iD_j indeterminancy indication

$R_7 = R_S \bullet R_{nond}$

$$\mu_{R_7}(p, D_j) = \underset{S_i}{MIN\,MAX}\{\ \mu_{R_S}(p, S_i);\ \mu_{R_{nond}}(S_i, D_j)\} \quad (3.7)$$
$$\nu_{R_7}(p, D_j) = \underset{S_i}{MAX\,MIN}\{\nu_{R_S}(p, S_i);\ \nu_{R_{nond}}(S_i, D_j)\}$$

where $\nu_{R_{nond}}(S_i, D_j) = 1 - \ \nu_{R_{nond}}(S_i, D_j)$.

if we consider some reasonable criteria for the above three indications in order to determine the lablel of disease, physicians ma y reach an excellent decision.

4. Simlarity degre based on IFS distance

We can define Hamming IF distance between IFSs A and B:

$$2 \cdot d_{H \cdot IFS(X)}(A,\ B) = \sum_{k=1}^{N}\{|\mu_A(x_k) - \mu_B(x_k)| + |\nu_A(x_k) - \nu_B(x_k)|\}$$

where $A, B \in IFS(X)$ and $x_i \in X$,

$$2 \cdot d(x_i) = |\mu_A(x_i) - \mu_B(x_i)| + |\nu_A(x_i) - \nu_B(x_i)|$$

and $2 \cdot d_{H \cdot IFS(X)}(A, B) = \sum_{i=1}^{N} d(x_i)$.

We define IFS distance between A and B as 1/2N $\frac{1}{N} d_{H \cdot IFS(X)}(A, B) = \frac{1}{2N} \sum_{i=1}^{N} d(x_i)$

IFS relations between symptoms and diseases are determined by physicians and his present knowledge of medical sciences. Suppose that the following are established as the prototypes of symptom-disease relations for (S_i, D_j): $\langle (S_i, D_j), \mu(S_i, D_j), \nu(S_i, D_j)\rangle$ $i = 1, \cdots, m$, $j = 1, \cdots, n$.

The observed symptoms of the patient p are as follows;

$\langle (p, s)\mu_{R_s}(p_i, s), \nu_{R_s}(p_i, s)\rangle$ for each $s_i \in S$, $i = 1, \cdots, m$.

IFs distance between (P, S_i) and (S_i, D_j) is defined as

$$\nu(D_j) = \frac{1}{2m} \sum_{i=1}^{m} |\mu(S_i, D_j) - \mu_{R_s}(P, S_i)| + |\nu(S_i, D_j) - \nu_{R_s}(P, S_i)|)$$

$$D = \{\langle D_j, \nu(D_j)\rangle \mid D_j \in D\},\ j = 1, \cdots, n$$

We can find same $\nu(D_j)$ under the constant level, which will be determined by the experts.

5. Diagnostic models for headache

Seventy-six percent(76%) of women and 57% of men are reported to experience at least one significant headache per month, and over 90% have experienced a headache in their lifetime[15]. Headache is a frequent presenting complaint in the emergency department and it is worthy of analyzing the interview chart. We have already established the interview chart for twelve categories of headache based on [15,17]. This chart consists of 92 multiple-choices in 20 items and a patient ought to answer one of multiple-choices in each item.

In our simulated data 600 patients are typically classified in twelve groups. The data matrix F consists of 600 rows and 92 columns [13,3,14]. By dual scaling we can obtain three solutions which explain the information of data. In these solutions we can find major symptoms related to each of twelve labels of headache and these are nearly consistent with the physician's knowledge and experience. Twelve fuzzy trapezoidal numbers, that is, twelve fuzzy labels of headache, can be inferred by the physician's knowledge and the estimated fuzzy neural linear regressions. If a patient checks a headache evaluation format, we can predict the three weights of a new patient by neural linear regressions and find the fuzzy label of headache as well as its major related symptoms. NFDDH-1 consists of interview chart of headche, twelve fuzzy labels and related symptoms, fuzzy neural linear regressions.

We will establish three inference methods with IFS-related headache data to determine the label of headache, so-called NFDDH-2. We will combine two systems as NFDDH. More details will be shown in PART 2.

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