



Mining Patient Information Using Triangular Fuzzy Logic

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Abstract- The clinical trial analysis is a main objective of medical treatment. Medical practitioner takes decision about patient's health, according to the clinical trial reports. Most of the clinical trial reports and results are in vagueness form. Researchers discover the knowledge from the clinical trials by using datamining techniques. Data preparation is essential process in datamining. In data preparation process, the vagueness value of clinical data has to be consolidated. The fuzzy logic assists to formalize the vagueness value and prepare the data for mining the knowledge. Fuzzy membership function exercises the vagueness value that is in the range between 0 and 1. The objective of this paper is to fuzzify the patient data using triangular membership function and mining the valuable information. The output of triangular membership function shows the fuzzified clinical data.

Keyword: Datamining, FuzzyLogic, Fuzzy Set, Trials

I. INTRODUCTION

Clinical data mining is one of the new domains in the clinical informatics [9][10]. The large amount of data collects in clinical trials. In the clinical data, the laboratory results and reports are in vagueness form [1]. When Data mining techniques apply into clinical dataset, the vagueness values restrict the knowledge discovery and decision making becomes fail [3]. Fuzzy logic is well suit to handle the vagueness value and deals with Boolean logic. Fuzzy set are viewed as a generalization of classical sets. The classical set is defined by crisp boundaries. Fuzzy set is defined by its ambiguous boundaries. Its properties are described by its membership function $\mu(x)$. Membership function helps to change the classify set into fuzzy set. In our proposed method, the fuzzy logic is applied over into the clinical dataset [8]. Triangular membership function assists to fuzzify the clinical data and mine more knowledge about patient medical details [1].

II. TRIANGULAR MEMBERSHIP FUNCTION

The triangular curve is a function of a vector, x , and depends on three scalar parameters [2][8], a , b , and c , as given by

$$\mu_{\underline{A}}(x : a, b, c) = \begin{cases} \frac{x-a}{b-a} & a < x \leq b \\ \frac{x-b}{c-b} & b < x \leq c \\ 0 & \text{otherwise} \end{cases}$$

The parameters a and c locate the "feet" of the triangle and the parameter b locates the peak.

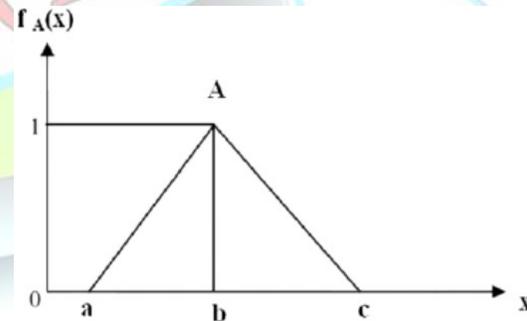


Fig1. Triangular membership function

The three main basic features involved in characterizing membership function are the following.

Core: The core of a membership function for some fuzzy set \underline{A} is defined as that region of universe that is characterized by complete membership function in



the set \underline{A} . The core has elements x of the universe such that $\mu_A(x) = 1$

Support: The support of a membership function for some fuzzy set \underline{A} is defined as that region of universe that is characterized by non membership function in the set \underline{A} . The support comprises elements x of the universe such that $\mu_A(x) > 0$

Boundary: The support of a membership function for some fuzzy set \underline{A} is defined as that region of universe containing that have a non zero but not complete membership function in the set \underline{A} . The boundary comprises those elements x of the universe such that

$$0 < \mu_A(x) < 1$$

III. PROPOSED METHOD

The analysis of clinical trials is too complex due to the vagueness value. So the valuable information becomes uncertainty when apply the datamining in the clinical trial dataset. The vagueness value discarded the accuracy of knowledge discovery. For avoiding this issue, in our proposed method applies the fuzzy logic into the clinical trial dataset when prepare the data for mining process. Generally, the laboratory reports and trial results are in crisp set format. The crisp set with their operations and properties are expressing the classical logic which leads to attain the vagueness results [6][9]. So the decision making becomes hard and fails in better knowledge discovery. The fuzzification is the process of transforming the crisp set into fuzzysset. For fuzzifying the clinical trial data, in our proposed method applies the triangular membership function. It's consolidated the vagueness value and converts into fuzzy set. Table 1 shows the sample clinical trial dataset. The boundary values have to be setup for all attributes except PatientID, Gender and Blood group attributes. The membership value [0,1] of each attribute values associate with boundary value. For example, if patient causes diabetes disease, the blood sugar metric value is important for diagnosis. The range value of blood sugar shown in below

Table 1. Blood sugar level chart

| Low | Normal | High |
|------|-----------|-------|
| < 80 | 80 <= 100 | > 100 |

The boundary value of sugar is based on the chart. In fig1, a, c are boundary value and b is core value. Therefore a=80, b=100 and c=320 (maximum value). In table 2, the sugar level of PatientID is 230. The fuzzification executes as per equation which derived in section 2. The implementation is given below

$$\begin{aligned} \text{Triangle } (230:80,100,320) &= (230-100) / (100-80) \\ &= 130/20 \\ &= 6.5 \\ &= (320-230) / (320-100) \\ &= 90/220 \\ &= 0.40 \end{aligned}$$

$$\begin{aligned} f(x) &= \max(\min(6.5, 0.40), 0) \\ &= 0.40 \end{aligned}$$

Figure 2 shows the result in the triangular membership shape.

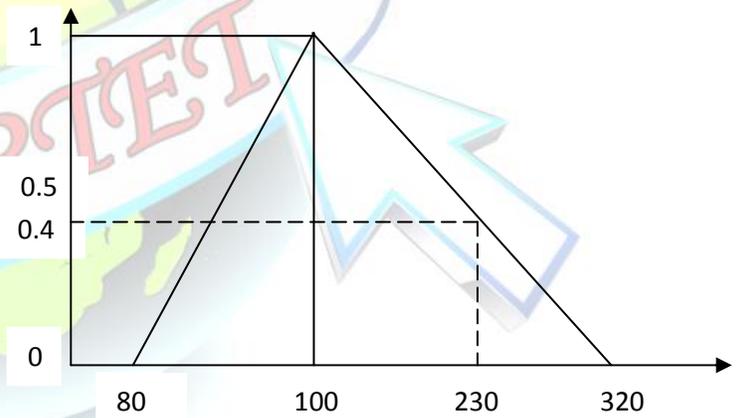


Fig2. Indication of fuzzy value in triangular membership shape

The fuzzy value of sugar metris230 is 0.4. It is observed that the calculation, the PatientID 116 causes diabetes in severe condition. The result has suggested, the patient ID 116 has to be taken treatment immediately. This formulation applies into values of all attributes except PatientID, Gender and Blood group attributes.



IV EXPERIMENTAL RESULT.

Our proposed method is applied over sample clinical dataset. In sample dataset of following attributes such as Patient ID, Gender, Age, Blood Group, Weight, Fever (F⁰C), Sugar and BloodPressure (BP). The Sample dataset has shown in the below table. In table 2, the attribute name ID represent the patient ID, 'G' represent the Gender, 'B' represent the Blood group, 'W' represent the weight, 'A' represent the age, 'BP' represent the Blood Pressure, 'F' represent the Fever (F⁰C) and 'S' represent the Sugar.

Table2. Sample clinical dataset

| P-ID | Age | Gen | BG | W | S | F | BP |
|------|-----|-----|----|----|-----|-----|-----|
| 111 | 18 | M | 5 | 54 | 108 | 101 | 90 |
| 112 | 32 | M | 1 | 65 | 123 | 104 | 80 |
| 113 | 43 | M | 3 | 70 | 116 | 97 | 60 |
| 114 | 54 | F | 2 | 84 | 94 | 90 | 100 |
| 115 | 65 | F | 7 | 66 | 82 | 107 | 110 |
| 116 | 36 | M | 3 | 66 | 237 | 107 | 120 |
| 117 | 47 | F | 1 | 72 | 109 | 92 | 140 |
| 118 | 68 | M | 6 | 81 | 58 | 100 | 105 |
| 119 | 79 | F | 2 | 69 | 71 | 100 | 100 |
| 120 | 40 | M | 7 | 40 | 85 | 99 | 86 |

Let a,b,c are membership variables as shown in the Fig 1.The boundary and core value of membership assign into following attributes

BP = {a=60,b=100,c=200}

Fever(F⁰C) = {a=90,b=97,c=107}

Sugar={a=30,b=108,c=320}

Age= {a=18,b=54,c=90}

Weight= {a=40, b=54,c=92}

Blood Group= {a=0,b=4,c=8}

In sample data, fuzzify the values by using triangular member function. The result shows in the table3.

Table3. Fuzzy clinical dataset

| P-ID | Age | Gender | BloodGrp | Weight | Sugar | Fever | Blood Pre |
|------|--------|--------|----------|--------|--------|--------|-----------|
| 111 | 0.0 | 1 | 0.6666 | 1.0 | 1.0 | 0.6 | 0.75 |
| 112 | 0.3888 | 1 | 0.25 | 0.7105 | 0.9292 | 0.3 | 0.5 |
| 113 | 0.6944 | 1 | 0.75 | 0.5789 | 0.9622 | 1.0 | 0.0 |
| 114 | 1.0 | 0 | 0.5 | 0.2105 | 0.8205 | 0.0 | 1.0 |
| 115 | 0.6944 | 0 | 0.0 | 0.6842 | 0.6666 | 0.0 | 0.9 |
| 116 | 0.5 | 1 | 0.75 | 0.6842 | 0.3915 | 0.0 | 0.8 |
| 117 | 0.8055 | 0 | 0.25 | 0.5263 | 0.9952 | 0.2857 | 0.6 |
| 118 | 0.6111 | 1 | 0.3333 | 0.2894 | 0.3589 | 0.7 | 0.95 |
| 119 | 0.3055 | 0 | 0.5 | 0.6052 | 0.5256 | 0.7 | 1.0 |
| 120 | 0.6111 | 1 | 0.6666 | 0.0 | 0.7051 | 0.8 | 0.65 |

Search Record Press 1 to Continue

Exit Press 2

1

Enter Patient-ID: 112

| P-ID | Age | Gender | BloodGrp | Weight | Sugar | Fever | BP |
|--|--------|--------|----------|--------|--------|-------|-----|
| 112 | 0.3888 | 1 | 0.25 | 0.7105 | 0.9292 | 0.3 | 0.5 |
| Age : Teenage Bloodgroup : AB-ve Weight : Heavy Weight Fever : High – Need Treatment Sugar : Medium – Consult Doctor BP : Low BP – Need Treatment | | | | | | | |

Search Record Press 1 to Continue

Exit Press 2

1

Enter Patient-ID: 116

| P-ID | Age | Gender | BloodGrp | Weight | Sugar | Fever | BP |
|---|-----|--------|----------|--------|--------|-------|-----|
| 116 | 0.5 | 1 | 0.75 | 0.6842 | 0.3915 | 0.0 | 0.8 |
| Age : Young Adult Bloodgroup : A-ve Weight : Heavy Weight Fever : Very High - Immediate Treatment Sugar : High – Need Treatment BP : Medium – Consult Doctor | | | | | | | |

Search Record Press 1 to Continue

Exit Press 2

1

Enter Patient-ID: 118



| P-ID | Age | Gender | BloodGrp | Weight | Sugar | Fever | BP |
|------|--------|--------|----------|--------|--------|-------|------|
| 118 | 0.6111 | 1 | 0.3333 | 0.2894 | 0.3589 | 0.7 | 0.95 |

Age : Old
 Bloodgroup : A+ve
 Weight : Over Weight
 Fever : High – Need Treatment
 Sugar : Low - Need Treatment
 BP : Medium – Consult Doctor

Search Record Press 1 to Continue

Exit Press 2

1

Enter Patient-ID: 120

| P-ID | Age | Gender | BloodGrp | Weight | Sugar | Fever | BP |
|------|--------|--------|----------|--------|--------|-------|------|
| 120 | 0.6111 | 1 | 0.6666 | 0.0 | 0.7051 | 0.8 | 0.65 |

Age : Young Adult
 Bloodgroup : A+ve
 Weight : Under Weight
 Fever : Medium – Consult Doctor
 Sugar : Low - Need Treatment
 BP : Low BP – Need Treatment

[7] Hans-Jürgen Zimmermann, FuzzySets, Decision Making, and Expert Systems,Kluwer academic publishers,ISBN:978-94-010-7957-0.

[8] Salim Rezvani,Comparative of Two Triangular Fuzzy Sets with α -cut , Journal of Physical Sciences, ,2015,Vol. 20, 111-132 ,ISSN: 2350-0352.

[9] Vaghela, Chaitali; Bhatt, Nikita; Mistry, Darshana. (2015). A Survey on Various Classification Techniques for Clinical Decision Support System, International Journal of Computer Applications ,2015,vol.116,No.23.

[10] Rubén Romero Córdoba,Jose Ángel Olivás, Francisco Pascual Romero, Clinical Decision Support System for the Diagnosis and Treatment of Fuzzy Diseases,LNCS,Vol.9422,pp.128-138.

V CONCLUSION.

In our proposed method, fuzzy logic has applied into sample clinical dataset and addresses the uncertainty in clinical data and changed the vagueness values into fuzzy values by using triangular membership function. The fuzzified clinical data assist to discover more knowledge accurately. In future, Clinical data will be applied into trapezoidal membership function [4][5] for improving the performance of fuzzification.

REFERENCES.

[1] Liu, J. and Shiffman, R., (1997). Operationalization of clinical practice guidelines using fuzzy logic, Proceedings of AMIA Ann. Fall Symp., 283-287.

[2] Dubois, D. & Prade, H. (1982). A class of fuzzy measures based on triangular norms: a general framework for the combination of information, International Journal of General Systems 8: 43–61.

[3] Adlassnig, K-P. (1986), Fuzzy set theory in medical diagnosis, IEEE Tr. On Syst., Man, and Cybernetics 16(2),March/April, 260-265.

[4] Sanhita Banerjee , Arithmetic Operations on Generalized Trapezoidal Fuzzy Number and its Applications, Turkish Journal of Fuzzy Systems, 2012, Vol.3, No.1, pp. 16-44.

[5] Salim Rezvani, Mohammad Molani, Representation of trapezoidal fuzzy numbers with shape function, Annals of Fuzzy Mathematics and Informatics, 2014, ISSN: 2093-9310.

[6] AhmadTaherAzar,Aboul Ella Hassanien,Dimensionality reduction of medical big data using neural-fuzzy classifier, Soft Computing, April 2015, Volume 19, Issue 4, pp 1115-1127.