Applications of Fuzzy Theory on Health Care: An Example of Depression Disorder Classification Based on FCM

SEN-CHI YU
Center of Teacher Education
Huafan University
No.1, Huafan Rd., Shiding, Taipei County, Taiwan
Taiwan
fuzzyirt@yahoo.com

YUAN-HORNG LIN
Department of Mathematics Education
National Taichung University
140 Min-Shen Rd., Taichung City 403, Taiwan
Taiwan
lyh@mail.ntcu.edu.tw

Abstract: The purpose of this study is to apply fuzzy theory on health care. To achieve this goal, Beck Depression Inventory (BDI)-II was adopted as the instrument and outpatients of a psychiatric clinic were recruited as samples and undergraduates as non-clinical sample as well. To elicit the membership degree, we asked the subjects are free to choose more than one alternative for each item listed in BDI and, in turn, assign percentages on the chosen alternatives. Moreover, the sum of percentages of the chosen categories is restricted to 100%.We performed the possibility- based (fuzzy c-means, FCM) and probability-based classification (Wald's method and k-means) to classification of severity of depression. The scoring of BDI of subjects were analyzed by clustering analysis while the diagnose of depression-severity by a psychiatrist was used as the criterion to evaluate classification accuracy. The percentage of correct classification among FCM, Wald's method and k-means were compared. The analytical results show the Kendall's τ coefficient of FCM, Wald's method and k-means were .549, .316, and .395, respectively. That is, FCM exhibited a higher association between the original and classified membership than did Wald's and k-means methods. We concluded that FCM identified the data structure more accurately than the two crisp clustering methods. It is also suggested that considerable cost concerning prevention and cure of depression might be reduced via FCM.

Key-Words: fuzzy c-means, depression, fuzzy logic, psychological assessment.

1 Introduction and Motivation

A depressive disorder is an illness that involves the body, mood, and thoughts. It is a mood state characterized by a sense of inadequacy, a feeling of despondency, a decrease in activity or reactivity, pessimism, sadness and related symptoms [1]. Depression is among the most pervasive psychological problems accounting for 10.4% of all patients seen in the healthcare settings in the world. According to the National Institute of Mental Health [18] , 1 in 10 American adults—or approximately 21 million people—suffer from a depressive illness each year. Some study indicated that almost 20% of the U.S. population will experience a clinically significant episode of depression at some periods of their lives [12]. The economic cost for this disorder is high, but the cost in human suffering cannot be estimated. The screening, diagnosis and classification of depression are critical.

Self-reported psychological scales are most straightforward and important tools in various healthcare settings in the diagnosis and classification between different levels of depression.

Likert scales is the most popular psychological measurement schemes that depend on human judgment [17]. This scaling scheme assumes that the human observer is good at quantitative observation, and assign of numbers or objects to reflect degrees of traits or statements being measured [19]. In this scoring schema, subjects are asked to choose exact one alternative that describe whose state of mood. However, this schema disregard of that human thinking is multi-valued, transitional and analogue, instead of bi-valued, clear-cut, and digital. Therefore, to introduce fuzzy theory into traditional psychological measurement should be feasible for several reasons.

First, the alternatives presented in the options alongside the rating scales are not numerical variables. These alternatives are linguistic variables whose values are not precise numbers but words in human languages. For instance, "speed" is a linguistic variable if it takes a value such as slow, moderate or fast. Linguistic variables can approximately characterize phenomena that are too complex or too ill-defined to be describable in conventional quantitative terms. Linguistic variables are less specific but more comprehensive than numerical ones in daily life. For instance, a question about sadness adapted in the Beck Depression Scale II [5] such as "I did not feel sad," " I felt sad much of the time," " I felt sad all the time," and "I'm so sad or unhappy that I can't stand it," are linguistic variables since these terms are not clearly defined and no definite boundaries exist between, for example, "much of the time" and "all the time".

Furthermore, the distinctions between two adjacent alternatives may be so polarized or extreme that choosing one alternative to represent one's state is burdensome. Considering the example quoted above, the discrepancy between two adjacent alternatives such as "I did not feel sad," and "I felt sad much of the time" seems so strong that examinees who only felt sad occasionally would not be easily able to select an alternative. Under such circumstance, assuming someone entirely belongs to one particular alternative may be debatable. Such an assumption is a crisp set view originated in Aristotle's binary logic, where each individual can be dichotomized into member of a set (those who certainly belong to the set) and nonmember (those who certainly do not). Inheriting from this view, test constructors ask examinees to choose one alternative (set) in each item. However, people generally feel depressed, satisfied, happy or comfortable in the continuum within two opposing extremes rather than a yes-or-no dichotomy. Therefore, human thinking is multi-valued, transitional and analogue, instead of bi-valued, clear-cut, and digital. Fuzzy set theory, providing a systematic framework for dealing with the vagueness and imprecision in human thoughts, is a powerful tool to analyze and animate human thinking [10]. Nevertheless, few fuzzy set theory applications have been found in psychometric studies.

In contrast with the many engineering studies discussing possibility-based classification technique [9] [10], however, only a few such works have been published in psychological measurement [2] [3]. This study compared the accuracy of classification of depression severity among possibility- based (fuzzy c-means, FCM) [13]and probability-based classification (Wald's method and k-means).

2 Problem Formulation

Depressive disorders come in different forms. The forth edition of Diagnostic and Statistical Manual of Mental Disorders (DSM-IV) [4] is recognized as the classification system for researchers and clinical purpose. According to DSM-IV, the diagnose criteria of Depression Disorder includes nine symptoms (mood, interests, eating, sleep, motor activity, fatigue, self-worth, concentration, and death) as shown in Table 1.

These symptoms cause clinically important distress or impair work, social or personal functioning [14]. In this study, the patients were classified into clinical depression and remission according to psychiatrist (As shown in Table 2). Clinical depression refers to the patient who has had 5 or more of the above-mentioned symptoms in the same two weeks. In remission refers to patients who formerly met full criteria for Major Depressive Episode and now either have fewer than five symptoms or have had no symptoms for less than two months.

Table 1. Symptoms of Depression

1. Mood: For most of nearly every day, the patient reports depressed mood or appears depressed to others.
2. Interests: For most of nearly every day, interest or pleasure is markedly decreased in nearly all activities (noted by the patient or by others).
3. Eating and weight: Although not dieting, there is a marked loss or gain of weight (such as five percent in one month) or appetite is markedly decreased or increased nearly every day.
4. Sleep: Nearly every day the patient sleeps excessively or not enough.
5. Motor activity: Nearly every day others can see that the patient's activity is agitated or retarded.
6. Fatigue: Nearly every day there is fatigue or loss of energy.
7. Self-worth: Nearly every day the patient feels worthless or inappropriately guilty. These feelings are not just about being sick; they may be delusional.
8. Concentration: Noted by the patient or by others, nearly every day the patient is indecisive or has trouble thinking or concentrating.
9. Death: The patient has had repeated thoughts about death (other than the fear of dying), suicide (with or without a plan) or has made a suicide attempt.

Table 2. Classification of Depression

1. Clinical Depression: In the same 2 weeks, the patient has had 5 or more of the above-mentioned symptoms, which are a definite change from usual functioning.
2. Remission(Partial/ Full Remission): Partial Remission: Patients who formerly met full criteria for Clinical Depression and now either (1) have fewer than five symptoms or (2) have had no symptoms for less than two months. In Full Remission: The patient has had no material evidence of Major Depressive Episode during the past 2 months.

Table 3. Examples of Fuzzy Scoring

Alternative	Assigned Percentages	Degree-of -Membership	Traditional Scoring
1*	80 %	.8	1
2	20 %	.2	
3	0 %	0	
4	0 %	0	

Table 4. Examples of Fuzzy Scoring : Only One Category Chosen

Alternative	Assigned Percentages	Degree-of -Membership	Traditional Scoring
1*	100 %	1	1
2	0 %	0	
3	0 %	0	
4	0 %	0	

The psychological instrument in this study was the Chinese version of Beck Depression Scale II(C-BDI-II) [5]. BDI, specifically developed to address all of the nine DSM–IV criteria for a major depressive episode, is a self-reported instrument for measuring the severity of depression in adolescents and adults through items showing varying degrees of the main cognitive, affective, and physiological aspects of clinical depression. Participants circle the number (0 to 3) associated with the item that best describes how they had felt over the past two weeks. Traditionally, participants were asked to choose exact one alternative associated with the item that best describes how they had felt. However, to elicit the membership degree, we asked the subjects are free to choose more than one alternative for each item and, in turn, assign percentages on the chosen alternatives. Moreover, the sum of percentages of the chosen categories is restricted to 100%. The procedure of fuzzy scoring was shown in Table 3 and 4. The results of fuzzy scoring were utilized in clustering analysis while of psychiatry's diagnosis was used as the criterion to evaluation clustering accuracy.

The total sample used in this study consisted of participants recruited from two separate populations: (a) the clinical sample: 240 subjects were recruited from outpatients who visit the psychiatric clinic at Taipei Municipal Hoping Hospital and were diagnosed as having depression symptoms. (b) The non-clinical sample: 319 undergraduate students in Taiwan were recruited.

The self-reported instrument was

administrated by the researcher while the severity of depression was diagnosed by a psychiatrist. The severity of depression of outpatients was classified into Clinical depression or remission according to diagnose of the psychiatrist while the undergraduate sample was treated as non-clinical depression. The response pattern in self-reported instrument was analyzed via FCM, Wald's method, and k-means while the diagnosed severity of depression was treat as the criteria for comparisons of classification accuracy.

Clustering analysis is an "unsupervised" technique, that is, no prior information was given to judge about what the output should be or whether it is correct. However, to compare the difference between probability-based and possibility-based cluster analysis, the original group membership (non-clinical depression, remission, and clinical depression) were used as the criteria to evaluate which the cluster technique could accurately discover the structure of data. To attain this goal, FCM, Wald's method, and the k-means clustering method were utilized. The associations between classification results and original group membership resulting from different methods were compared.

3 Problem Solution

First, cluster validity indices were applied to determine the optimal cluster number (c) and exponential weight (m) in FCM [6]. In this study, two indices, partition coefficient (PC) and partition entropy (PE) were employed as the measure of cluster validity. PC is expressed as:

$$\mathrm{PC}=\sum_{k=1}^{n}\sum_{i=1}^{c}\frac{(\mu_{ik})^2}{n} \tag{1}$$

Where μ_{ik} denotes the degree to which subject k belongs to cluster i, and c denotes the cluster number. The maximum PC is found for the partition with the "most unambiguous" assignment [7]. Another cluster validity index, partition entropy, is expressed as:

$$\mathrm{PE} = -\frac{1}{n}\sum_{k=1}^{n}\sum_{i=1}^{c}\mu_{ik}\ln(\mu_{ik}) \tag{2}$$

Where μ_{ik} denotes the degree to which subject k belongs to cluster I, and c the cluster number. A partition with low entropy is preferred to one with high entropy [7].

Table 4. Summary of Cluster Validity

Index	Cluster Number (c)			
	C=2	C=3	C=4	C=5
PE	.955	.965*	.940	.932
PC	.080	.061**	.103	.117

* optimal cluster number according to PE
** optimal cluster number according to PC

The validity indices were computed by F-cut Fuzzy Partition Software [8], and are shown in Table 4. The optimal cluster number was searched using maximum PE and minimum PC. As presented in Table 4, the optimal cluster number is 3 with exponential weight 1.25. Therefore, FCM apply with cluster number = 3 for the proceeding analysis.

To identify the cluster technique which could discover the data structure most accurately, cluster number = 3 was assigned to FCM, Wald's method, and k-means method. To compute the association between original and classified membership, classified crisp membership in FCM was modified by assigning 0-or-1 membership to the cluster with the highest membership. Kendall's τ coefficient, which measures the relationships among variables and rank orders, was applied to measure the association between original and classified membership. The results of association analysis are shown in Table 5, Table 6 and Table 7 respectively.

Table 5. Classification Results (FCM)

	Classified Group (FCM)			Total
Original Group	1	2	3	
Non-clinical Depression (1)	229	82	8	319
Remission (2)	8	17	10	35
Clinical Depression (3)	35	86	84	205
Total	272	185	102	559
Kendall's τ coefficient	.549 (p<.001)			

Table 6. Classification Results (Wald's Method)

Original Group	Classified Group (FCM) 1	2	3	Total
Non-clinical Depression (1)	265	5	49	319
Remission (2)	23	7	5	35
Clinical Depression (3)	93	60	52	205
Total	381	72	106	559
Kendall's τ coefficient .316 (p<.001)				

Table 7. Classification Results (k-means)

Original Group	Classified Group (FCM) 1	2	3	Total
Non-clinical Depression (1)	244	4	71	319
Remission (2)	10	8	17	35
Clinical Depression (3)	52	60	93	205
Total	306	72	181	559
Kendall's τ coefficient .395 (p<.001)				

As presented in Table 5 to 7, the Kendall's τ coefficient of FCM was .549, that of Wald's method was .316, and that of k-means was .395 (p<.001). The analytical results demonstrate that FCM exhibited a higher association between the original and classified membership than did Wald's and k-means methods. That is, FCM identified the data structure more accurately than the two crisp clustering methods.

4 Conclusion

Traditional scoring of psychological is crisp logic in natural. That is, when endorsing an item, you can only choose exact one alternative to reflect your thought or feeling. However, human thinking or feeling is more fuzzy logic than crisp logic. Taking the item "Sadness" presented in BDI as an example, the four alternatives presented were "I do not feel sad", "I feel sad much of the time", "I am sad all the time", and "I am so sad or unhappy that I cannot stand it". Someone who only feels sad occasionally must choose between "I do not feel sad" (the first alternative) and "I feel sad much of the time" (the second alternative). However, the distinction between two adjacent alternatives is so polarized or extreme that selecting one alternative is burdensome. When a respondent is asked to choose precisely one alternative presented in the rating scales to describe his mood state or attitude, some force fitting and rounding off are inevitable.

To clarify whether fuzzy logic is more accuracy than crisp logic when applying to the investigation of a latent psychological constructs. Three classification techniques (FCM, k-means, and Wald's method) were applied. FCM is an unsupervised and multi-membership technique. To compare FCM with other crisp clustering methods, the results of FCM were modified in two ways. First, the original sample membership was taken as the criteria to evaluate the classification accuracy. Second, each classified group was assigned to the group that acquired the highest membership degree. That is, the membership degrees were "crispified" into binary values.

The primary aim of cluster analysis is to discover structure or information in data. With regard to psychological data, the results of clustering are intended to identify the structure inherent in latent psychological constructs. Traditional crisp clustering methods recognize and categorize patterns dichotomously. Nevertheless, these methods have some limitations when the data structure was based on possibility rather than probability. Human thinking, traits, attitude and natural language applied to denote human perceptions are based on multiple-value instead of binary logic [16]. Therefore, the membership of a particular group is a transition from 0 to 1 rather than a binary choice between 0 and 1 [11]. Considering the psychological latent construct [17] "depression" as an example, the depression state of a person is a transition from non-depressed to depressed. Therefore, whether a person belongs to the group "depression sufferers" is better represented by gradual membership rather than a yes-or-no dichotomy. This investigation justifies these theoretical inferences. Fuzzy-based FCM was found to yield stronger associations between original and classified groups than crisp-based clustering. Restated, FCM uncovers the information inherent in latent structure more accurately than crisp-based clustering.

References:

[1] N. S. Endler, S. D. Macrodimitris, and N. L. Kocovski, Controllability in Cognitive and Interpersonal Tasks: Is Control Good for You? *Personality and Individual Differences*, Vol. 29, 2000, pp.951-962.

[2] S. Yu, and M. Yu, Fuzzy Partial Credit Scaling: A more valid approach to scoring Beck Depression Inventory II. *Social Behavior and Personality*, 2007, (in press)

[3] S. Yu, and B. Wu, Fuzzy Item Response Model: A New Approach to generate membership function for psychological measurement. *Quality and Quantity*, 2007, (in press).

[4] American Psychiatric Association. *Diagnostic and Statistical Manual of Mental Disorders*, American Psychiatric Association, 1994.

[5] A. T Beck, R. A Steer, and G. K. Brown, *Manual for the Beck Depression Inventory–II*. Psychological Corporation, 1996.

[6] H. J. Zimmermann, *Fuzzy Set Theory and Its Applications*, Kluwer, 1996.

[7] F. Hoppner, F. Klawonn, R. Kruse, and T. Runkler, *Fuzzy Clustering Analysis*, John Wiley & Sons, 1999.

[8] Y. H. Lin, *F-cut: Fuzzy Partition Program* [software and manual], National Taichung University, Taiwan, 2003.

[9] B. Kosko. *Fuzzy thinking: The new science of fuzzy logic*. Hyperion, 1993.

[10] D. Dubios and H. Prade. *Fundamentals of fuzzy sets*. Kluwer, 2000.

[11] L. A. Zadeh. Fuzzy sets. *Information and Control,* Vol.8, 1965, pp.338-352.

[12] E. E. Beckham, and W. R, Leber. *Handbook of depression*. The Guildford Press, 1995.

[13] J. C. Bezdek. *Pattern recognition with fuzzy objective function algorithms*. Plenum Press, 1981.

[14] B. M. Byrne and P. Baron. Measuring adolescent depression: Test of equivalent factorial structure for English and French versions of the Beck Depression Inventory. *Applied Psychology: An International Review,* Vol.43, 1994, pp.33-47.

[15] T. J. Ross., J. M. Booker, and W. J. Parkinson. *Fuzzy logic and probability applications*. SIAM, 2002.

[16] S. J. Cheng and C. L. Hwang,. *Fuzzy multiple attribute decision making: Methods and applications*. Springer-Verlag, 1992.

[17] J. C. Nunnally and I. H. Berstein, *Psychometric theory*. McGraw-Hall, 1994..

[18] National Institute of Mental Health(2000). Depression. [On-line] Available: www.nimh.nih.gov/publicat/depression.cfm

[19] K. D. Hopkins, J. C.Stanley, & B. R. Hopkins. Education and psychological measurement and evaluation (7th ed.). Prentice Hall, 1990.

[20] S. Yu. Fuzzy partial credit scaling: Applying fuzzy set theory to scoring rating Scales. Unpublished doctoral dissertation, National Chengchi University, Taipei, Taiwan, 2005.

Acknowledgements:

The authors would like to thank National Science Council of Republic of China for the support given to this study. (Project Number: NSC-95-2413-H211-001)