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The implementation of z-numbers in fuzzy clustering algorithm for wellness of chronic kidney disease patients

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Abstract. By gleaning insights from the data, fuzzy clustering capable to learn from data, identify patterns and make decision with minimum human intervention. However, it cannot simply study in detail regarding the quality of data, particularly knowledge of human being. Since the data are collected through decision-makers, the quality and human knowledge of the particular data are crucial factors to be considered. Compared to classical fuzzy numbers, znumbers has ability to describe the human knowledge because it has both restraint and reliability part in its definition. Consequently, the implementation of z-numbers in fuzzy clustering algorithm is taken into consideration, where it has more authority to describe the knowledge of human being and extensively used in uncertain information development. Thus, there are two objectives of this paper; (i) to propose a reliable fuzzy clustering algorithm using z-numbers and; (ii) to cluster the Chronic Kidney Disease (CKD) patients based on the selected indicators to identify which cluster the patients belongs to (Cluster 0, Cluster 1, Cluster 2, Cluster 3 or Cluster 4) based on the membership functions defined. A case study of the CKD patients with the selected indicators is considered to demonstrate the capability of znumbers to handle the knowledge of human being and uncertain information and also will present the idea in developing a robust and reliable fuzzy clustering algorithm particularly in dealing with knowledge of human being using z-numbers.

1. Introduction

Machine learning algorithm forms a mathematical model based on sample data, known as training data, in order to make predictions or decisions (1) and categorized into supervised, semi-supervised, and unsupervised learning algorithm. Data mining is one of a field study within the machine learning which focused on exploratory data analysis through unsupervised learning (2). It involves analyzing large dataset to see pattern and trends from the information gathered (3). This information are extracted, tranformed and loaded to interpret knowledge related to the various field such as image mining, web mining, text mining, including anomaly detection, financial data analysis, medical data analysis, social network analysis and so forth. Several data mining techniques are applied in real world phenomena such as regression, association, classification, and clustering.

Clustering is a data mining technique which is used to form data that having similarity in the pattern. It can be categorised as unsupervised learning technique which is widely used in pattern recognition, market strategies, image processing and data analysis (4). The data information used for these various areas are massive and sometimes include the uncertain and imprecise data especially when involving knowledge, experience, linguistic words and so forth. To handle the uncertain and imprecise knowledge, fuzzy logic was introduced by Zadeh in 1965 (5)(6). Fuzzy logic is applied in the algorithm and assign a membership degree for each data. In the meantime, one of the most used fuzzy clustering algorithm is the Fuzzy c-Means clustering (FCM) algorithmn. It was developed by (7) in 1973 and improvised by (8) in 1981. In fuzzy c-means algorithm, the reciprocal of distances is used to decide the centers of the cluster. The centroid of a cluster is calculated as mean of all points and weighted by their degree of belonging to the cluster. This algorithm gives better results because it has fuzzy logic that can model complex systems such as human knowledge (5)(9).

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Due to concern expressed about the fuzziness and imprecise data information especially in human knowledge, fuzzy numbers can be used to describe these data properly (10)(11)(12). Yet, the reliability of the information in a decision environment is very significant. Classical fuzzy numbers might have limitations in describing the reliability of the information (13). Zadeh (14) extended the concept of fuzzy numbers by introducing the concept of z-number. A z-number is an ordered pair of fuzzy numbers that restricts the evaluation and reliability of human judgment. In literature, the researchers have been done as upgraded classical fuzzy numbers to z-numbers. Kang et al. (15) proposed a method to convert z-numbers into fuzzy numbers, where the second component is defuzzified into a crisp number. Later, several researches proposed useful methods using z-numbers concept (16)(17)(18)(19). Since z-number can describe levels of human judgment, then it also can be effectively applied to decision-making problem (20). Though, there is a lack of study combining the z-numbers approach with the fuzzy clustering or fuzzy c-means algorithm.

Meanwhile, Chronic kidney disease (CKD) has become a global health issue and a lot of researches have been done by using CKD data and analysis. One of the methods used in analyzing CKD data is data mining. Data mining approaches have become important for health industry especially in making a decision from the big clinical data. The different technique in data mining used by several researchers like classification, clustering, association, and regression (21)(22)(23)(24) are used to identify and predict disease evolution to make analysis and decision (25). In addition, there is yet, to date, a study that using CKD data analysis to cluster their patients according to the indicators selected based on the factors that affects their wellness. Hence, this study aims to propose two objectives; firstly to propose a reliable fuzzy clustering algorithm (fuzzy c-means) with the implementation of z-numbers and secondly, to cluster the CKD patients based on the selected indicators to identify which cluster the patients belongs to (Cluster 0, Cluster 1, Cluster 2, Cluster 3 or Cluster 4) based on the membership functions defined.

The remainder of this paper is organized as follows. In Section 2, some definitions and concepts are introduced. In Section 3, the steps of calculating z-numbers data and the clustering method using fuzzy c-means are proposed. In Section 4, the proposed method is applied to the CKD patients' data. Section 5 concludes the paper.

2. Preliminaries

In this section, some concepts and definitions used in this paper are introduced.

2.1 Fuzzy set

Definition 1 A fuzzy set A is defined on a universe X may be given as:

$$A = \{\langle x, \mu_A(x) \rangle | x \in X\}$$
 [1]

Where $\mu_A: X \to [0,1]$ is the membership function A. The membership value $\mu_A(x)$ describes the degree of belongingness of $x \in X$ in A (26).

Definition 2 A trapezoidal fuzzy number \tilde{A} can be defined by a quadruplet $\tilde{A} = (a_1, a_2, a_3, a_4)$, where the membership can be determined as the following equation and can be described as Figure 1.

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < a_1, \\ \frac{x - a_1}{a_2 - a_1}, & a_1 \le x \le a_2, \\ 1 & a_2 \le x \le a_3, \\ \frac{x - a_3}{a_3 - a_4}, & a_3 \le x \le a_4, \\ 0, & x > a_4 \end{cases}$$
[2]

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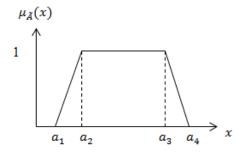


Figure 1. A trapezoidal fuzzy number

2.2 Z-number

Concept of z-number defined by Zadeh (14) is associated with an uncertain variable Z as an ordered pair of fuzzy numbers, (A, R) where A is a fuzzy subset of the domain X of the variable Z and R is a fuzzy subset of the unit interval. The concept of z-numbers is proposed to provide a basis computation with numbers which are not totally reliable. A z-number can be used to represent the information about an uncertain variable where A represents a value of the variable and R represents an idea of certainty or probability (27).

Definition 3 A z-number is an ordered pair of fuzzy numbers denoted as $Z = (\tilde{A}, \tilde{R})$. The first component \tilde{A} , a restriction on the values, is a real-valued uncertain variable X. The second component \tilde{R} is a measure of reliability for the first component. The membership function for component \tilde{A} and \tilde{R} are as follows which can be described as Figure 2.

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{(x-a_1)}{(a_2-a_1)} & if & a_1 \leq x \leq a_2 \\ 1 & a_2 \leq x \leq a_3 \\ \frac{(a_4-x)}{(a_4-a_3)} & if & a_3 \leq x \leq a_4 \\ 0 & otherwise \end{cases}$$

$$\mu_{\tilde{R}}(x) = \begin{cases} \frac{(x-b_1)}{(b_2-b_1)} & if & b_1 \leq x \leq b_2 \\ 1 & b_2 \leq x \leq b_3 \\ \frac{(b_4-x)}{(b_4-b_3)} & if & b_3 \leq x \leq b_4 \\ 0 & otherwise \end{cases}$$

[3]

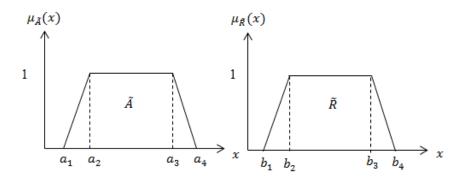


Figure 2. A z-number in the form of trapezoidal fuzzy numbers

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2.3 Fuzzy c-Means Algorithm

Fuzzy c-Means (FCM) is an algorithm of clustering which allows one piece of data to belong to two or more clusters. Aforementioned, this algorithm is developed by Dunn in 1973 (7) and improved by Bezdek in 1981 (8). It is based on the minimization of the following objective function:

$$J_{m} = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \|X_{i} - C_{j}\|^{2}, \qquad 1 \le m \le \infty$$
 [4]

Where u_{ij} represents the degree of membership element x_i in the cluster j. The squared element is the Euclidian distance between i^{th} data and j^{th} center of the cluster. Completed every iteration update of the membership function and center of clusters c_i is calculated as follows:

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\left\| X_i - C_j \right\|}{\left\| X_i - C_k \right\|} \right)^{\frac{2}{m-1}}}$$
 [5]

Where centers of clusters can be calculated as follows:

$$C_{j} = \frac{\sum_{i=1}^{N} u_{ij}^{m} \cdot x_{i}}{\sum_{i=1}^{N} U_{ij}^{m}}$$
 [6]

This iteration will stop when $\max_{ij} \left\{ \left| u_{ij}^{(k+1)} - u_{ij}^{(k)} \right| \right\} < \varepsilon$, where ε is a termination criterion between 0 and 1, whereas k are the iteration steps. This procedure converges to a local minimum or a saddle point of J_m . The steps of the algorithm are calculated as follows:

Step 1: Initialization of $U = [u_{ij}] matrix$, $U^{(0)}$.

Step 2: At k-steps: Calculate the of centers vectors $C^k = [c_j]$ with $U^{(k)}$.

$$C_{j} = \frac{\sum_{i=1}^{N} u_{ij}^{m} x_{i}}{\sum_{i=1}^{N} U_{ij}^{m}}$$

Step 3: Update $U^{(k)}$, $U^{(k+1)}$.

$$u_{ij} = \frac{1}{\sum_{k=1}^{C} \left(\frac{\|X_i - C_j\|}{\|X_i - C_k\|} \right)^{\frac{2}{m-1}}}$$

Step 4: If $||U^{(k+1)} - U^{(k)}|| < \varepsilon$, then STOP; otherwise return to Step 2.

3. Methodology

This section describes the methodology on the calculating z-numbers information and fuzzy c-means algorithm. There are three main processes involved that consist of data evaluation, fuzzy clustering and reporting. Figure 3 depicts the workflow of the process involved.

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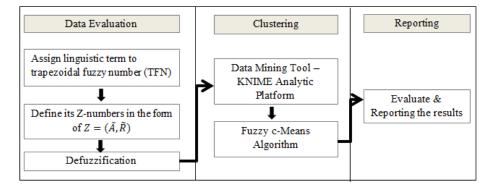


Figure 3. The workflow of the process involved.

3.1 First Stage: Data Evaluation

The collected data are firstly evaluated and defined using z-numbers. There are two steps involved which are:

Step 1: Evaluate the data and define its z-numbers.

The collected data are represented in the form of linguistic variable that needs to be converted into classical fuzzy number under the frame of fuzzy set. The first component of the z-number, \tilde{A} , is converted to a trapezoidal fuzzy number $\tilde{A} = (a_1, a_2, a_3, a_4)$ and the second component \tilde{R} (the reliability) can be converted also into trapezoidal fuzzy number.

Step 2: Converting z-numbers to generalized fuzzy numbers.

Z-numbers are converted to generalized fuzzy numbers using (28). The reduction process to convert z-numbers to type-1 fuzzy numbers are proposed using intuitive vectorial centroid (IVC). The formula for IVC can be computed as follows:

$$IVC(\tilde{x}_{\tilde{A}}, \tilde{y}_{\tilde{A}}) = \left(\frac{2(a_1 + a_4) + 7(a_2 + a_3)}{18}, \frac{7h_{\tilde{A}}}{18}\right)$$
[7]

where \tilde{x} : the centroid point on the horizontal x-axis

 \tilde{y} : the centroid point on the vertical y-axis

 (\tilde{x}, \tilde{y}) : the centroid coordinate of fuzzy number \tilde{A} .

 $h_{\tilde{A}}$: the height \in [0,1].

Assume a z-number = $Z = (\tilde{A}, \tilde{R})$. Let $\tilde{A} = \{\langle x, \mu_{\tilde{A}}(x) \rangle | x \in [0,1]\}$ and $\tilde{R} = \{\langle x, \mu_{\tilde{R}}(x) \rangle | x \in [0,1]\}$, $\mu_{\tilde{A}}(x)$ and $\mu_{\tilde{R}}(x)$ are trapezoidal membership function. To convert z-numbers to generalised fuzzy numbers, the reliability component on x-coordinate are defuzzified into crisp number using the first part of equation [7]. Then, add the weight of reliability component to the restriction component. To defuzzify the data, by using coordinate (x,y) from equation [7] again and calculate using Euclidean Distance proposed by (29).

$$R(\tilde{A}) = \sqrt{(\tilde{x}^2 + \tilde{y}^2)}$$
 [8]

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3.2. Second Stage: Fuzzy Clustering

After all the data have been defuzzified, then it will imported to the KNIME analytic platform software to continue with the fuzzy clustering process. In this stage, there are only one step involved:

Step 3: Clustering process using Fuzzy c-Means algorithm.

The defuzzified value from Step 2 then imported to the KNIME software as the machine learning tool to calculate the clustering process using Fuzzy c-Means algorithm. KNIME is an open source data analytics, reporting and integration platform (30). KNIME integrates various components for machine learning and data mining through its modular data pipelining concept. A graphical user interface allows the assembly of nodes for data processing, modeling, data analysis, and visualization. KNIME tool is the only one that comes with the GUI based Fuzzy clustering node for the data mining (31).

3.3 Third Stage: Evaluation and Reporting the results

In KNIME, the results can be executed by right-clicking the Fuzzy c-Means node. The results to be considered in this research are as follows:

- *Cluster Membership* option A new tab will appear and all the data will be clustered according to their membership value. Lower membership value is clustered together where it has lower degree points than the cluster center. The near to the cluster center means that it has a higher degree of its membership to its cluster.
- Statistic View option where it shows the WithinClusterVariation result and the BetweenClusterVariation result, which are the indicators for 'good' clustering.

In addition, to make sure how good the performance of the clustering algorithm is, another two results will be added:

- Confusion Matrix to see how many actual results match the predicted results.
- Cohen's kappa score refers to the correct predictions occurring by chance.

4. Case Study

A case study of the quality of life for chronic kidney disease (CKD) patients is presented here. The data were collected via a questionnaire from a total of 71 respondents who are having CKD for more than one year. Basically, the questionnaire consists of eight indicators that evaluate the quality of life for each patient which are physical functioning (A1), role-physical (A2), bodily pain (A3), general health (A4), vitality (A5), social-functioning (A6), role-emotional (A7) and mental health (A8). Belows are the calculations, figures, and tables, following the steps proposed in section Methodology above.

First stage: Data Evaluation.

Step 1: Evaluate the data and define its z-numbers.

The data are evaluated and the linguistic value for each indicator are assigned as in Table 1 and 2 below (32)(33).

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. Table 1. Linguistic variables and trapezoidal fuzzy numbers (TFN) value

Linguistic variables	Trapezoidal Fuzzy Numbers
Never (N)	(1,1,1,2;1)
Almost Never(AN)	(1,2,2,3;1)
Sometimes (S)	(2,3,3,4;1)
Often (O)	(3,4,4,5;1)
Almost Always (AA)	(4,5,5,5;1)

Table 2. Reliability linguistic variable and its z-numbers value

Linguistic variables	Trapezoidal Fuzzy Numbers
Very Low (VL)	(0,0,0.25;1)
Low (L)	(0.25, 0.25, 0.5; 1)
Medium (M)	(0.5,0.5,0.75;1)
High (H)	(0.75,0.75,1;1)
Very High (VH)	(0.75,1,1;1)

Step 2: Converting z-numbers to generalized fuzzy numbers.

The evaluated data are converted to a generalized fuzzy number using equation [7] respectively. Table 3 below shows the calculations of 10 respondents only out of 71 respondents.

Table 3. Generalized fuzzy number for physical functioning (A1) indicator.

Respondent	Generalized fuzzy numbers					
	(a1,	a2,	a3;	h)	x	у
1	1.4790	1.8077	2.6841	1	2.2094	0.3889
2	1.3695	2.1364	3.1224	1	2.5442	0.3889
3	1.4242	2.0268	2.9580	1	2.4255	0.3889
4	2.1911	3.1224	3.9988	1	3.4571	0.3889
5	2.0816	2.8485	3.6702	1	3.1741	0.3889
6	1.8625	2.7389	3.6702	1	3.1072	0.3889
7	2.0816	3.0128	3.9441	1	3.3750	0.3889
8	1.9172	2.7937	3.6702	1	3.1345	0.3889
9	1.1503	1.4242	2.3555	1	1.8594	0.3889
10	0.9860	1.2599	2.2459	1	1.7225	0.3889

The generalized fuzzy numbers are calculated and defuzzified for its x and y using equation [7]. The results for 10 respondents are shown in Table 4.

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Table 4. Defuzzified value for all indicators

Indicator	- A1	A2	A3	A4	A5	A6	A7	A8
Respondent	AI	AZ	AS	A4	AS	AU	AI	A0
1	2.2434	2.3874	1.9563	2.3033	2.3468	3.6907	1.6994	2.1715
2	2.5737	2.6309	3.3640	2.4655	2.8749	2.3874	2.3874	2.6309
3	2.4564	2.8749	2.8749	2.9111	2.6851	3.2371	2.9183	2.4144
4	3.4789	3.9768	3.3640	2.6700	3.3640	3.0378	3.3640	3.8542
5	3.1978	2.4144	2.3874	1.9324	2.6309	1.8134	1.6994	2.6580
6	3.1314	2.6309	2.8749	3.2552	3.1193	3.6907	2.6038	3.1193
7	3.3973	3.3640	2.3874	3.9087	4.2222	3.2009	2.9726	3.8542
8	3.1586	3.1193	2.8749	2.7122	3.1193	2.3874	2.5821	2.3874
9	1.8997	1.7421	1.9563	2.1954	2.6309	2.7122	2.0423	2.8749
10	1.7658	1.7421	1.5293	1.6237	1.7421	1.5293	1.5293	1.5293

Second Stage: Fuzzy Clustering

Step 3: Clustering process using Fuzzy c-Means algorithm.

The defuzzified data from Step 2 were then imported to KNIME software using Excel Reader node and cluster the data using Fuzzy c-Means node. These two nodes are connected in the workflow. For this model, the number of clusters assigned are five with a maximum repeated process to 99 iterations and assigned as cluster_0 to cluster_4 as in Figure 4 below.

Third Stage: Evaluation and Reporting Results

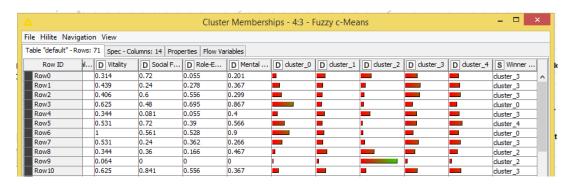


Figure 4. Output for 10 respondents from Fuzzy c-Means

The results can be viewed in the cluster memberships when right-clicked at the Fuzzy c-Means node after executed the model. Figure 4 shows the cluster memberships for 10 respondents. The memberships value are represented in horizontal bars.

From the output, Row0 is for respondent 1, Row1 is for respondent 2, and so on until the 71st respondents. The last column on the right-hand-side title *Winner Cluster* representing the cluster of which respondent belongs to. For example, Row0 respondent belongs to cluster_3 and Row1 respondent belongs to cluster_3 and so on. Lower membership value is clustered together where it has lower degree points than the cluster center. The near to the cluster center means that it has a higher degree of its membership to its cluster. To decide which cluster the data belongs to, the summation of degree membership need to be equal to 1 and iterates until its reach maximum number (34). So, from the Figure 4, Row0 clustered in cluster_3 because it has higher membership degree to its cluster

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center. Same goes to the other respondents and the results of the CKD patients clustered are shown in Figure 5 below.

	No. of respondents
cluster_0	14
cluster_1	16
cluster_2	10
cluster_3	21
cluster_4	10
Total	71

Figure 5. CKD patients clustered to its cluster group.

Referring to Figure 5, out of 71 respondents, there are 14 CKD patients clustered in cluster_0, 16 CKD patients are clustered together in cluster_1 and so on. This indicates that the CKD patients are clustered together in the same cluster because they have the similarity on their opinion of the quality of life and wellness of themselves, as a patients, when they answered the questionnaires.

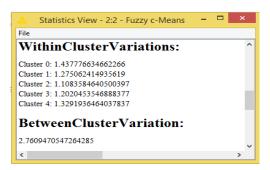


Figure 6. Statistic View

From the statistic view results above, the WithinClusterVariation measure the goodness or how good the algorithm was. The small the value shows the good the algorithm is. The values for cluster_0 until cluster_4 shows the small value and this indicates that the clustering process is good.

Figure 7 shows the scatter matrix plots based on the output in Figure 5.

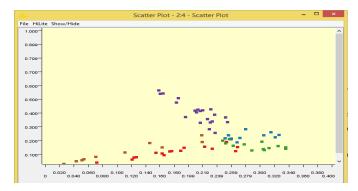


Figure 7. Scatter matrix plot for the CKD patients after being clustered.

Finally, to measure how good the performance of the clustering algorithm, the confusion matrix is used to see how many actual results match the predicted results. From this matrix, the accuracy and Cohen's kappa result are shown. Accuracy refers to the number of correct predictions or how precise

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the dataset is being clustered. Cohen's kappa refers to the correct predictions occurring by chance. From Figure 8, the accuracy from Fuzzy c-Means algorithm obtained is 88.889% and Cohen's kappa value 0.856 indicates that the performance of the algorithm is good.

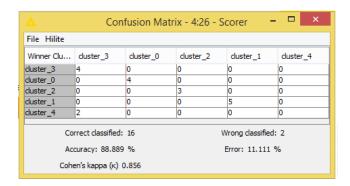


Figure 8. Confusion Matrix, Accuracy and Cohen's kappa scores

5. Conclusion

A clustering algorithm is used to analyze data to predict its type of class. The implementation of z-numbers to the data collected shows that this algorithm has capability to handle the uncertain information gave by the respondents more accurate since it has the reliability part in each of the fuzzy numbers. These reliable data are then clustered using Fuzzy c-Means and gave the better results. From the results, the CKD patients are clustered to its cluster group and shows the capability of z-numbers to handle the knowledge of human being and incorporated well with the fuzzy c-Means. In this research study, the clustering algorithm used is Fuzzy c-Means only. The work can be extended by considering other clustering algorithms such as K-means, Hierarchical clustering and so forth. Future research also can be done by considering other CKD indicators such as adding decision maker's point of view for better analysis.

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