Fuzzy Rating Framework for Knowledge Management

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Abstract

In this work we deploy five phases of the Case-based Reasoning in a fuzzy rating framework, which illustrates a holistic knowledge management method including eliciting expert's experience into case base, validating the expert's expertise in knowledge-consistency level, aggregating the judgments of weighted experts into final ratings, solving new problem by retrieving the relevant cases, and retaining the adapted case into case base once the experience had been learned. The main contribution of this framework is to explore a novel measure of knowledge-consistency level (KC ratio) for identifying experts in performance-rating domain. The would-be experts' own judgments were used to validate their knowledge qualities. Moreover, the framework results in an optimal consensus for the performance rating with the help of experts.

1. Introduction

Making good use of experiences, one can attain the competitive advantage. This experience-based learning model has also become a key issue for organizations nowadays. Hence, to accumulate experiences from human experts, known as knowledge management, has drawn a lot of attention. Various methods have been studied in different disciplines and made contribution to different phases of knowledge management. Among these methodologies, Case-based reasoning (CBR) is particularly appropriate in weak theory domains where the principles are not well defined. The core of CBR is the case base which stores a collection of experiences. If a new problem occurs, CBR retrieves the most similar k relevant exemplar of the target case from the case base, uses that case to suggest a solution, evaluates the proposed solution and updates the system by learning from this experience. In the light of the aforementioned processes, López de Mántaras et al [1] suggested that the Fuzzy sets might be favorable in case representation to allow for uncertain values. Thus, we integrate Fuzzy sets techniques with CBR methodology for knowledge management.

Converging experts' judgments toward knowledge establishment involves in the processes of group decision-making. These processes indicate a sequence of transformations to aggregate individual judgments into a consensus. In fuzzy environments, experts usually express their judgments by using numerical values assessed in a unit interval. However, there are some decision problems where experts are not able to assign exact numerical value. In such cases, an alternative linguistic assessment should be considered. Most reports dealt with either numerical or linguistic model. We shall work on both numerical and linguistic model mutually. Regarding to knowledge validation, previous studies focused on data [2]. But the inconsistencies in data do occur and adversely affect the performance of knowledge management. Herrera-Viedma *et al.*[3] examined the intra-personal consistency with fuzzy preference relations while Shanteau *et al.*[4] argued that internal consistency is a necessary but not sufficient condition for expertise. Accordingly, we validate the knowledge by examining personal consistency and group discrepancy mutually.

This article consists of 7 sections. Section 2 discusses knowledge elicitation and representation. Section 3 explores the knowledge validation. Section 4 presents the fuzzy similarity measurement together with fuzzy *k*-NN retrieval for knowledge reuse. Knowledge refinement achieved through knowledge consensus is depicted in section 5 and the maintenance of knowledge in section 6. Finally, section 7 offers conclusion and future works.

2. Phase I: Knowledge representation

Several techniques have been developed to elicit the knowledge from experts. The key issue is related to the optimized relationships to allow the experts to reason about a problem and traverse the mental distance between symptom and solution. Here, in order to have an optimized relationship path (knowledge), both fuzzy numbers and linguistic labels are used together for case representation.

Step 0: Determination of the linguistic label set

The number of linguistic labels used for linguistic assessment variable $\tilde{A} = \{\tilde{A}_1, \tilde{A}_2, \ldots, \tilde{A}_i\}$ is 5 in this paper, including $\tilde{A}_1$=worst, $\tilde{A}_2$=bad, $\tilde{A}_3$=even, $\tilde{A}_4$=better, and $\tilde{A}_5$=good.

Step 1: Elicitation of the linguistic judgment matrix

Let expert review the raw data x_{kj} and assign l_{kj} as the corresponding assessment in linguistic labels for the jth feature of the kth case, where j=1, ., n, k=1, .., m. And, he can further predict the overall performance rating $l_{k,n+1}$, l_{kj} and $l_{k,n+1} \in \tilde{A}$. After expert's assessment, we transform the original quantity data into quality data by eliciting expert's tacit knowledge as expressed in (1).

$$\begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}_{m\times n} \Rightarrow \begin{pmatrix} l_{11} & \cdots & l_{1n} \, l_{1,n+1} \\ \vdots & \ddots & \vdots \\ l_{m1} & \cdots & l_{mn} \, l_{m,n+1} \end{pmatrix}_{m\times(n+1)} \quad (1)$$

Step 2: Calculation of the weight of each feature

The contribution of each feature to the final rating is ambiguous in the expert's perception. Hence, we use genetic algorithms (GAs) to construct an optimal or near-optimal weight vector. The classification accuracy rate (CAR) of the test case set had been used in the fitness function, it is expressed as:

$$\max CAR = \frac{1}{m}\sum_{i=1}^{m} CA_k \quad (2)$$

where $CA_k = \begin{cases} 1 \; if \; O(T_k) = O(S_{j*(k)}), \\ 0, \quad\quad otherwise \end{cases}$

and $S_{j*(k)} = \max\left(Sim\left(\mathbf{v}^R, \mathbf{v}^I\right)\right)$

where $S_{j*(k)}$ is the most similar retrieved case $\mathbf{v}^R$ with testing case $\mathbf{v}^I$ and $O(T_k)$ is the target output of the test case $\mathbf{v}^I$. If CAR is equal to 1, then the corresponding chromosome is optimal.

Step 3: Definition of the membership functions for corresponding linguistic labels

Let the expert assign l_{ij} , m_{ij} and u_{ij}, which denoted the lower, middle and upper bounds of linguistic assessment label $\tilde{A}_{ii}$ of feature j respectively. And the membership functions of corresponding symmetric triangular fuzzy number can be defined as follows.

$$\mu_{\tilde{A}_i}(x_{kj}) = \begin{cases} (x_{kj} - l_{ij}) / (m_{ij} - l_{ij}) & l_{ij} \le x_{kj} < m_{ij} \\ (u_{ij} - x_{kj}) / (u_{ij} - m_{ij}) & m_{ij} \le x_{kj} \le u_{ij} \\ 0, & otherwise \end{cases} \quad (3)$$

Step 4: Establishment of the fuzzy performance matrix

We applied the raw data x_{kj} to the corresponding membership functions in sequence. Thus the performance degree of each feature x_{kj} of a given case can be obtained by:

$$r_{kj} = \sum_{i=1}^{t} norms(\tilde{A}_{ij})\left(u_{\tilde{A}_{ij}}\left(x_{kj}\right)\right) \quad (4)$$

And $$norms(\tilde{A}_{ij}) = \frac{m_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (5)$$

norms() function will normalize the fuzzy numbers $\tilde{A}_{ij}$ into range [0, 1] as dominant values which are proportional to the bounded interval of the real line. And the overall performance rating for a given case can now be obtained by weighted aggregation as

$$r_k = \sum_{j=1}^{n} w_j r_{kj} \quad (6)$$

where w_j represents the weight of the feature j, and sum to 1. The weight vector obtained from GAs was specified in step 2. Finally, we derive the fuzzy performance matrix, as shown in (7), from the corresponding fuzzy numbers, which were parallel to the linguistic judgment matrix; it would manifest the tacit knowledge resided in the experts' mind.

$$\begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix}_{m\times n} \Rightarrow \begin{pmatrix} r_{11} & \cdots & r_{1n} \, r_{1,n+1} \\ \vdots & \ddots & \vdots \\ r_{m1} & \cdots & r_{mn} \, r_{m,n+1} \end{pmatrix}_{m\times(n+1)} \quad (7)$$

3. Phase II: Knowledge validation

While the linguistic judgment matrix captures the expert's tacit knowledge, the fuzzy performance matrix derived from the membership functions of the triangular fuzzy numbers approximates the expert's perception. Shanteau [4] argued that the knowledge consistency of expert's judgments should be held. Due to these two matrixes rooted in the same expert's knowledge, we examined the self-consistency of the expert's judgments by comparing the following two matrixes.

$$\begin{pmatrix} l_{11} & \cdots & l_{1n} & l_{1,n+1} \\ \vdots & \ddots & & \vdots \\ l_{m1} & \cdots & l_{mn} & l_{m,n+1} \end{pmatrix}_{m\times(n+1)} \Leftrightarrow \begin{pmatrix} r_{11} & \cdots & r_{1n} & r_{1,n+1} \\ \vdots & \ddots & & \vdots \\ r_{m1} & \cdots & r_{mn} & r_{m,n+1} \end{pmatrix}_{m\times(n+1)} \quad (8)$$

If l_{kj} in linguistic judgment matrix is equal to $\tilde{A}_{ij}$, then we define the distance *diff*(E) shown in (9) as the average of to difference between the corresponding value r_{kj} and the dominant values of $\tilde{A}_{ij}$.

$$diff(E) = \frac{1}{m\times n}\sum_{k=1}^{m}\sum_{j=1}^{n}\sqrt{\left(r_{kj} - norms(\tilde{A}_{ij})\right)^2}, if\ l_{kj} = \tilde{A}_{ij} \quad (9)$$

diff(E), the distance between linguistic judgment matrix and fuzzy performance matrix, indicates the knowledge inconsistency level of the expert held. Since the smaller the difference was the greater the knowledge consistency connoted, the self-consistency level of the expert can now be obtained in (10).

$$SC(E) = 1 - diff(E) \quad (10)$$

4. Phase III: Knowledge retrieval

4.1. Case indexing with fuzzy similarity index

In fuzzy-sets operations, similarity of cases is computed based on the membership functions of the fuzzy sets associated with the features of cases. Euclidean distance notion would be used in this paper. The input case $\mathbf{v}^I$ vector is considered to contain n features' real values, while the retrieved case $\mathbf{v}^R$ from fuzzy performance matrix herein contains n obverse fuzzy degrees plus one final performance rating r_{n+1} as a solution. If the membership degree of each feature x_j^I of fuzzy cases $\mathbf{v}^I$ is derived using equation (4), then we can transform the input case vector to a new fuzzy case vector. After transformation, we adapt Wang's simple and reliable method [5] to derive equation (11) for case similarity measure.

$$sim(\mathbf{v}^R, \mathbf{v}^I) = \sum_{j=1}^{n} w_j \times \left[1 - \left|r_j^R - r_j^I\right|\right] \quad (11)$$

where $1 - \left|r_j^R - r_j^I\right|$ is regarded as the similarity degree of fuzzy cases $\mathbf{v}^R$ and $\mathbf{v}^I$ on the feature *j*. The $sim(\mathbf{v}^R, \mathbf{v}^I)$ is the weighted average of the similarity degree of $\mathbf{v}^R$ and $\mathbf{v}^I$, called fuzzy similarity index. The range of $sim(\mathbf{v}^R, \mathbf{v}^I)$ is from 0 to 1, which corresponds to the different similarity degree. $sim(\mathbf{v}^R, \mathbf{v}^I)$ =1 indicates that the two fuzzy cases are identical; otherwise there exists a difference between these two fuzzy cases.

4.2. Case retrieval with fuzzy k-NN

Once the case similarity index has been defined, the suitable solution can be expected in the column l_{n+1}^R cohered with the column r_{n+1}^R of the retrieved case. Therefore, an effective retrieval of useful prior case would be significant. We incorporated fuzzy membership into the classical nearest neighbor similarity function. There are some advantages of using fuzzy indexing and retrieval. First, fuzzy *k*-NN defines classes so that a significant reduction in feature space and problem complexity can be achieved. Second, fuzzy *k*-NN supports the flexibility of case matching to allow multiple indexing of a case on features with different degrees of membership. It should be noted that the case's memberships in the resulting classes must sum to one. Analogous fuzzy nearest prototype algorithm [6] has been adopted in the proposed system for not only the computational simplicity but also the desirable membership assignments.

5. Phase IV: Knowledge refinement

The case base established in phase I was based on individual expert's knowledge. If more experts were available, then the fair knowledge can be drawn from group consensus. Thus, knowledge refinement process is presented in a context of multi-person decision making, known as knowledge consensus measurement.

Assumed a finite set of expert $E = \{E^1, E^2, ..., E^e\}$ and each expert E^e presents his/her linguistic assessment on feature *j*, case *k* is $l_{kj}^e \in \tilde{A}_{ij}$. Following step 1 thru step 4 in Phase I and the same concept in phase II, we can obtain the linguistic judgment matrixes and fuzzy performance matrixes from experts and the self-consistency level of each expert as specified in (12) and (13), respectively.

$$\begin{pmatrix} l_{11}^e & \cdots & l_{1n}^e & l_{1,n+1}^e \\ \vdots & \ddots & & \vdots \\ l_{m1}^e & \cdots & l_{mn}^e & l_{m,n+1}^e \end{pmatrix}_{m\times(n+1)} \Leftrightarrow \begin{pmatrix} r_{11}^e & \cdots & r_{1n}^e & r_{1,n+1}^e \\ \vdots & \ddots & & \vdots \\ r_{m1}^e & \cdots & r_{mn}^e & r_{m,n+1}^e \end{pmatrix}_{m\times(n+1)} \quad (12)$$

$$SC(E^e) = 1 - diff(E^e) \quad (13)$$

where $diff(E^e)$ indicates the self-inconsistency level of the eth expert held

$$diff(E^e)=\frac{1}{m\times n}\sum_{k=1}^{m}\sum_{j=1}^{n}\sqrt{\left(r_{kj}^e-norms(\tilde{A}_{ij})\right)^2},if\ l_{kj}^e=\tilde{A}_{ij} \quad (14)$$

Generally, the consensus is achieved by subjective assignment of the weights of the experts or the contribution of group members [7]. However, the self consistency and consensus reliability were necessary but not sufficient conditions for expertise [4]. Therefore, we combine self consistency with group discrepancy to define the weight of expert as follows.

$$dis(E^e) = 1/m\left(\sum_{k=1}^{m} r_k^e - \left(1/p\sum_{e=1}^{p} r_k^e\right)\right) \quad (15)$$

where $dis(E^e)$ denotes the group-discrepancy of the eth expert in the temporary consensus. $1/p\sum_{e=1}^{p} r_k^e$ is the equal weighted average for case k, Thus it is apparent that the smaller the group-discrepancy is, the greater the group-consistency connotes. Then KC ratio,

$$KC(E^e) = SC(E^e)/dis(E^e) \quad (16)$$

denotes knowledge consistency of the eth expert. It is large when the judge coheres with himself and group mutually but is small if the judge is either less self-consistent or lower group-consistent. Finally, the weight of the eth expert $w(E^e)$ can be obtained in terms of knowledge consistency as follows.

$$w(E^e) = KC(E^e)/\sum_{e=1}^{p} KC(E^e) \quad (17)$$

And $\sum_{e=1}^{p} w(E^e) = 1$

Appling the weights of the experts to knowledge consensus measurement, the final fuzzy performance rating for a given case can now be refined by weighted average.

$$\begin{pmatrix} r_{11}^e & \cdots & r_{1n}^e\, r_{1,n+1}^e \\ \vdots & \ddots & \vdots \\ r_{m1}^e & \cdots & r_{mn}^e\, r_{m,n+1}^e \end{pmatrix}_{m\times(n+1)} \Rightarrow \begin{pmatrix} r_{11}^c & \cdots & r_{1n}^c\, r_{1,n+1}^c \\ \vdots & \ddots & \vdots \\ r_{m1}^c & \cdots & r_{mn}^c\, r_{m,n+1}^c \end{pmatrix}_{m\times(n+1)} \quad (18)$$

where $r_{kj}^c = \sum_{e=1}^{p} w(E^e) r_{kj}^e$ is the weighted average. After achieving the consensus, the refined matrix would be close to realities.

6. Phase V: Knowledge maintenance

Generally, the greater the density of cases, the greater the chances of having redundant cases occurred. A suitable case remedy policy should be formulated for deleting cases that are highly reachable from others. Since the environment is turbulent nowadays, the predicting criteria will vary from time to time. We just implement the necessary processes from phase I thru phase IV to update the case base once the criteria fluctuate or new experiences have been learned.

7. Conclusion and future works

We have developed a practical framework to accomplish the essential processes of knowledge management and provide the accurate performance prediction. Moreover, the self consistency level $SC(E)$ can return to the expert for referral. A novel measure of knowledge consistency level for identifying experts in performance-predicting domain has also been indicated. And the knowledge refinement can proceed to reach an optimal consensus by aggregating the judgments of weighted experts into the overall ratings as the solution. Further study is currently undertaken on other possible domains to demonstrate the effectiveness of the proposed framework.

8. References

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