Enhancing Business Decision Making Through Actionable Knowledge Discovery Using an Hybridized MCDM Model

Lucky Ikuvwerha[1(✉)], Taiwo Amoo[1(✉)], Victor Odumuyiwa[1(✉)], and Olufunke Oladipupo[2]

[1] Department of Computer Sciences, University of Lagos, Akoka, Lagos, Nigeria
ogagatilucky@gmail.com, amootaiwo01@gmail.com, vodumuyiwa@unilag.edu.ng

[2] Department of Computer Science, Covenant University, Ota, Ogun, Nigeria
funke.oladipupo@covenantuniversity.edu.ng

Abstract. In recent years, with the increase in the usage of internet-enabled electronic devices and information systems, the upsurge and availability of volumes of high dimensional data have become one of the sources of high business value. The need for businesses to make informed decisions by leveraging on the patterns from the multi-dimensional data have become paramount. However, the major issue is whether or not the patterns can optimize business decision making process to increase profit. Hence, there is need for actionable knowledge discovery (AKD). Therefore, this paper proposed an hybridized interval type-2 fuzzy Multi Criteria Decision Making (MCDM) model for evaluating patterns based on three subjective interestingness measure which are unexpectedness, actionability and novelty. The interval type-2 Fuzzy Analytical Hierarchy Process (AHP) was employed to weigh the patterns and Compensatory AND approach was utilized for ranking the patterns using the three subjective interestingness measures. The proposed model depicts its applicability in identifying and ranking the patterns which are more relevant for enhancing business decision making.

Keywords: Actionable knowledge discovery
Fuzzy analytic hierarchy process · Multi-criteria decision making

1 Introduction

Business organizations are using Information and Communication Technologies (ICT) to gather and store data in high dimensional volumes. All these data hold valuable knowledge in form of patterns or trends, which can be used to advance business strategies in today's competitive business environment. Businesses require measures that will drive productivity, increment profits, improve customer satisfaction and the likes. One of the processes that can be employed to achieve this is knowledge discovery process. Knowledge Discovery Process is defined as non-trivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in

V. Odumuyiwa et al. (Eds.): AFRICOMM 2017, LNICST 250, pp. 262–271, 2018.
https://doi.org/10.1007/978-3-319-98827-6_25

data [1]. However, the patterns discovered can be so many, and as a result may not be actionable, that is, the end user cannot act on it or take action. Hence, the domain knowledge of the experts is required to extract useful and actionable patterns. This has led to the paradigm shift from traditional Knowledge discovery process to Actionable knowledge discovery process (AKD).

Actionable knowledge discovery is based on interestingness measure. Interestingness measure can be generally divided into two categories: objective measure which is based on the strength of the statistical method of the data mining criteria and subjective measure based on the user's beliefs or expectations of the particular problem domain. In recent years, different approaches have been proposed as an extension of knowledge discovery processes to transcend to better actionable patterns [2, 3]. However, these studies lack consideration for the inter-uncertainties/imprecision that may be involved in preference elicitation from decision makers [6]. Therefore, using a model that will improve the subjective interestingness measure is of great importance.

MCDM models are techniques that analyse decision makers' preferences concurrently in the presence of multiple and conflicting criteria to arrive at an optimized decision out of all alternatives concerned [4]. However, the classical MCDM approaches cannot handle the imprecision and ambiguities that are involved in decision making processes [8]. Consequently, as an extension of the classical MCDM approaches, the hybridization of type-1 fuzzy and the interval type-2 fuzzy set was proposed [4, 7]. Therefore, in this paper, a novel interval type-2 fuzzy MCDM model based on explicit data intervals of the decision makers is proposed for the subjective interestingness measure of discovered patterns.

2 Preliminaries

This section describes the basic concept of actionable patterns and the interval type 2 fuzzy definitions used in this paper.

Definition 1.1. Actionability of a pattern: Given a pattern *P*, its actionable capability *act*() is described as to what degree it can satisfy both technical and business interestingness.

$$\forall\, x \in I, \exists P{:}\, x.tech\_int(P) \wedge x.biz\_int(P) \rightarrow act(\mathrm{P}) \tag{1}$$

where x.tech_*int*(*P*) is the technical or objective interestingness measure and *x.biz_int* (*P*) is the business or subjective interestingness measure.

Definition 1:2. The type-2 fuzzy set *A* can be represented as follows [5]:

$$\tilde{\tilde{A}} = \int_{x \in X} \int_{u \in J_x} \mu_{\tilde{\tilde{A}}}(x, u)/(x, u) \tag{2}$$

where J_x = [0, 1] and $\int$ denote union over all admissible x and u.

Definition 1.3. If all $\mu_{\tilde{\tilde{A}}}(\mathrm{x}, \mathrm{u}) = 1$, then $\tilde{\tilde{A}}$ is called an interval type-2 fuzzy set. An interval type-2 fuzzy set $\tilde{\tilde{A}}$ can be considered as a special case of a type-2 fuzzy set, which is represented as [8] :

$$\tilde{\tilde{A}} = \int_{x \in X} \int_{u \in J_x} 1/(\mathrm{x}, \mathrm{u}), \tag{3}$$

where $\mathrm{J_x} = [0, 1]$ and $\int$ denote union over all admissible x and u.

Definition 1.4. The upper membership function (UMF) and the lower membership function (LMF) of an interval type-2 fuzzy set are type-1 membership functions, respectively [6].

$$\begin{aligned}\tilde{\tilde{A}}_1 = \left(\tilde{A}_i^U, \tilde{A}_i^L\right) =& \left(\left(a_{i1}^U, a_{i2}^U, a_{i3}^U, a_{i4}^U, H_1\left(\tilde{A}_i^U\right), H_2\left(\tilde{A}_i^U,\right)\right),\right.\\ &\left.\left(a_{i1}^L, a_{i2}^L, a_{i3}^L, a_{i4}^L, H_1\left(\tilde{A}_i^L\right), H_2\left(\tilde{A}_i^L\right)\right)\right)\end{aligned} \tag{4}$$

where $\tilde{\mathrm{A}}_\mathrm{i}^\mathrm{U}$ and $\tilde{\mathrm{A}}_\mathrm{i}^\mathrm{L}$ are type1 fuzzy sets, $a_{\mathrm{i1}}^{\mathrm{U}}, a_{\mathrm{i2}}^{\mathrm{U}}, a_{\mathrm{i3}}^{\mathrm{U}}, a_{\mathrm{i4}}^{\mathrm{U}}, a_{\mathrm{i1}}^{\mathrm{L}}, a_{\mathrm{i2}}^{\mathrm{L}}, a_{\mathrm{i3}}^{\mathrm{L}}, a_{\mathrm{i4}}^{\mathrm{L}}$ are the reference points of the interval type-2 fuzzy $\tilde{\tilde{A}}_i$; $H_j(\tilde{A}_i^U)$ denotes the membership value of the element $a_{i(j+1)}^U$ in the upper trapezoidal membership function $\tilde{A}_i^U; 1 \leq j \leq 2, H_j\left(\tilde{A}_i^L\right)$ denotes the membership value of the element $a_{i(j+1)}^L$ in the lower trapezoidal membership function $\tilde{\tilde{A}}_i^L; 1 \leq j \leq 2, H_j(\tilde{\tilde{A}}_i^L) H_1(\tilde{\tilde{A}}_i^U) \in [0,1], H_2(\tilde{\tilde{A}}_i^U) \in [0,1], H_1(\tilde{\tilde{A}}_i^L) \in [0,1], H_2(\tilde{\tilde{A}}_i^L) \in [0,1]$ and $1 \leq i \leq n$. The arithmetic operations between the trapezoidal interval type-2 fuzzy sets is described in [7]. The defuzzification of trapezoidal type-2 fuzzy sets (DTraT) proposed by [8] was defined for the defuzzification process.

3 Methodology

In this section, the methodological flow is described as follows:

3.1 Stage One: Pattern Generation

At this stage, rules were generated from the decision tree. These are the rules that show how the decision tree was able to classify the model based on the label. We used these rules as patterns because it is possible to gain more insight from them on how the decision tree was able to classify the model [3].

3.2 Stage Two: Pattern Ranking

The rules generated which were represented as patterns were passed into this stage as input to be ranked using the three subjective interestingness measures (unexpectedness, actionability and novelty) as a combined measure. Consequently, the interval type-2 fuzzy Analytical Hierarchy and Compensatory AND approach were proposed for weighting the criteria and ranking the patterns accordingly as follows:

Interval Type 2 Analytical Hierarchy Process
The AHP was proposed by [9]. The proposed main steps for defining criteria importance are as follows:

Step 1: Collect data intervals for all the words used in eliciting criteria importance from the decision makers (DM).
Step 2: Perform the pre-processing of all the data intervals for each linguistic term (word) based on [6].
Step 3: Translate the data intervals from all subjects for each word to their respective UMF and LMF fuzzy parameters using [6] and plot the fuzzy set for each word.
Step 4: Construct a fuzzy pair-wise comparison matrix between criteria for each decision maker, k using the interval type-2 fuzzy numbers derived in **Step 3.**
Step 5: Perform arithmetic operations on the pair-wise comparison matrices of the evaluators/DMs and derive an average.
Step 6: Defuzzify the averaged type-2 fuzzistics pair wise comparison matrix, A_{ave} using DTrat defuzzification method [8].
Step 7: Perform the Eigenvector technique on the defuzzified comparison matrix A to derive final weight of each criterion.

The criteria weights of the interval type-2 fuzzy AHP are inputs to the ranking MCDM method below to finally rank the patterns concerned. The patterns were ranked according to their interestingness based on the following criteria: unexpectedness, actionability and novelty.

Compensatory AND Approach: The compensatory AND is defined by Zimmerman and Zynso [10] as:

$$\mu_\theta = \left(\prod_{i=1}^{m} \mu_i\right)^{1-\gamma} * \left(1 - \prod_{i=1}^{m}(1-\mu_i)\right)^{\gamma} \quad 0 \leq \mu \leq 1;\ 0 \leq \gamma \leq 1. \tag{5}$$

If it is desired to introduce different weights for the sets in question, μ_i and $1 - \mu_i$ could for instance be replaced by $\mu_i = \left(\frac{\vartheta_i}{n}\right)^{\delta_i}$ and $1 - \mu_i = \left(1 - \left(\frac{\vartheta_i}{n}\right)\right)^{\delta_i}$ where ϑ_i are the (raw) membership values, δ_i, their corresponding weights and $\gamma = 0.6$, which indicate the degree of compensation. The sum of weights δ_i should be equal to the number of sets connected. That means $\sum_i \delta_i = m$.

4 Experiments

The dataset used in this research is from the University of California, Irvine (UCI) benched mark dataset [11]. The dataset contains 45,211 records, 17 attributes and a class label attributes. This dataset is related to the direct marketing campaigns from a Portuguese bank which was done by phone call. The goal is to predict if the customer will subscribe or not for a new deposit package. This study uses RapidMiner studio version 7.0 edition for model training and testing. The decision tree obtained from the dataset is shown below:

Decision Tree
duration > 827.500
| pdays > 495.500: no {no = 2, yes = 0}
| pdays $\leq$ 495.500: yes {no = 744, yes = 1036}
duration $\leq$ 827.500
| age > 89.500
| | age > 93.500: no {no = 2, yes = 1}
| | age $\leq$ 93.500: yes {no = 0, yes = 5}
| age $\leq$ 89.500: no {no = 39174, yes = 4247}
Several patterns were generated as shown in Table 1:

Table 1. Rules generated as patterns

Rules generated
if duration $\leq$ 410.500 and month = aug and pdays $\leq$ 0 and duration > 183.500 then no (1444 /113)
if duration $\leq$ 410.500 and month = aug and pdays $\leq$ 0 and duration $\leq$ 183.500 and job = admin. then no (174 /3)
if duration > 410.500 then no (4801 /2742)
if duration $\leq$ 410.500 and month = apr then no (1959 /331)
if duration $\leq$ 410.500 and month = aug and pdays > 0 and duration > 159.500 then yes (107 /146)
if duration $\leq$ 410.500 and month = aug and pdays > 0 and duration $\leq$ 159.500 and duration > 106.500 and job = admin. and pdays > 100.500 then no (12 /0)

Three rules as patterns from the above rules with higher right classification and lower wrong classification covered by the rule were chosen. These patterns are labelled pattern A to C according.

$$\text{Pattern A: if duration} \leq 410.500 \text{ and month} = \text{aug andpdays} > 0 \text{ and}$$
$$\text{duration} > 159.500 \text{ then product} = \text{yes}$$

$$\text{Pattern B: if duration} \leq 410.500 \text{ and month} = \text{aug and pdays} \leq 0 \text{ and}$$
$$\text{duration} \leq 183.500 \text{ and job} = \text{technician then product} = \text{no}$$

$$\text{Pattern C: if duration} \leq 410.500 \text{ and month} = \text{jun and contact} = \text{unknown and}$$
$$\text{duration} \leq 368.500 \text{ and age} > 24.500 \text{ then product} = \text{no}$$

where pdays is numbers of day when the client was last contacted. Duration is the time in seconds when the client last contacted.

After generating the patterns, we proceeded to weigh the patterns: Assume we have k decision makers, $\{DM_1, DM_2 \ldots DM_k\}$ and also set of criteria F where F = {Unexpectedness(UN), Novelty(NO), Actionability(AC)} which are established to be hierarchical in nature. Also, a definition of a set T of linguistic terms, T = {Moderately more important = MI, Extremely more important = EXI, Equally more important = E, Very Strongly more important = VSI, Strongly more important = SI} was proposed for eliciting criteria importance from decision makers as shown in Table 2.

Table 2. Pairwise comparison matrix obtained from DM 1

	AC	NO	UN
AC	E	MI	1/SI
NO	1/MI	E	EXI
UN	SI	I/EXI	E

Additionally, a set X of linguistic terms, X = {Dissatisfied = D, Very satisfied = VS, Fair = F, Very Dissatisfied = VD, Satisfied = S} was defined for evaluating the patterns by the decision makers as shown in Table 3. Lastly, a set Y of competing alternatives which comprise of 3 patterns were proposed where Y = {Pattern A, Pattern B, Pattern C}.

Table 3. Performance matrix of pattern A

	AC	NO	UN
DM 1	F	F	F
DM 2	S	S	S

In order to rank the patterns Y in relation to subjective interestingness, the following MCDM approaches, interval type-2 fuzzy analytical hierarchy process and the Compensatory AND approach were utilized. Using Steps 1-7 in the Interval Type-2 Fuzzy Analytical Hierarchy Process, the linguistic terms of the pairwise comparison matrix are transformed to their respective (UMF) and (LMF) parameters using Table 4. Similarly, their respective interval type-2 plots for each word are depicted in Fig. 1, and the determination of weights of the criteria, F are derived as shown in Table 5.

In deriving the ranked patterns with respect to its subjective interestingness, the Compensatory AND approach was utilized as defined in Eq. (5). The set X of linguistic terms, X = {Dissatisfied = D, Very satisfied = VS, Fair = F, Very Dissatisfied = VD, Satisfied = S} was defined for evaluating the patterns by the decision makers as shown in Table 3. Consequently, set X was transformed to their corresponding interval type-2 fuzzy numbers using Table 6 and aggregation was done using arithmetic operations defined in Eq. (4). Defuzzification was carried out accordingly using the DTrat approach. Furthermore, their respective interval type-2 plots for each word in X are depicted in Fig. 2. Then, using Eq. (5), the patterns were ranked as depicted in Table 7.

Table 4. Words used for eliciting criteria importance (weights) and their interval type-2 fuzzy numbers

Linguistic labels	Corresponding interval type-2 fuzzy numbers
Equally important	(0,0,1.1918,4.6077; 1,1)(0,0,0.1376,1.9747; 1,1)
Moderately more important	(2.5858, 4, 4.5, 5.4142; 1,1)(3.7929, 4.3333, 4.3333,5.2071; 0.7643,0.7643)
Strongly more important	(4.4822,5.7500,7,8.4142; 1,1)(5.8136,6.2857,6.2857,6.8107; 0.4949, 0.4949)
Very strongly more important	(6.0858,7.2500,8.2500,9.1692; 1,1) (7.3308,7.7773,7.7773,8.0864; 0.4857,0.4857)
Extremely more important	(6.7088,9.7706,10,10; 1,1)(9.3418, 9.9541,10,10; 1,1)

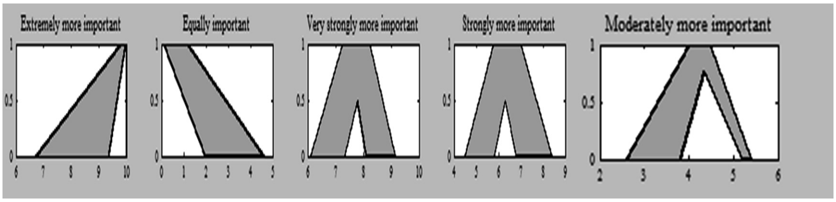

Fig. 1. Plots of the fuzzy sets for each word used in eliciting criteria performance

Table 5. Weight derived for each criterion

Criteria	Weight	Rank
Actionability	0.2941	2
Novelty	0.4261	1
Unexpectedness	0.2798	3

Table 6. Words used for eliciting performance of each pattern and their interval type-2 fuzzy number

Linguistic labels	Corresponding interval type-2 fuzzy numbers
Very Dissatisfied	(0, 0,0.2753,3.9495; 1,1)(0,0,0.0918,1.3165; 1,1)
Dissatisfied	(0.98,2.5,3.25,5.0178; 1,1)(2.29,2.8,2.8,3.18; 0.5757, 0.5757)
Fair	(2.98,4.5,5.25,7.01; 1,1)(4.39,4.71,4.71,5.10; 0.697,0.697)
Satisfied	(4.27,6,7.5,9.22; 1,1)(6.21,6.75,6.75,7.20; 0.4697,0.4697)
Very satisfied	(6.70,9.77,10,10; 1,1)(8.6835, 9.9082, 10,10; 1,1)

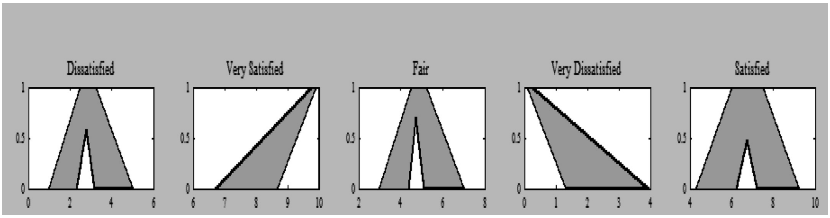

Fig. 2. Plotting of the fuzzy sets for each word used in eliciting patterns' performance

Table 7. The final ranked patterns using the interval type-2

Pattern	Compensatory AND values	Rank
Pattern A	0.4066	3
Pattern B	0.4375	2
Pattern C	0.4604	1

Table 8. The final ranked patterns using the type-1 fuzzy

Pattern	Compensatory AND values	Rank
Pattern A	0.5227	2
Pattern B	0.5137	3
Pattern C	0.5654	1

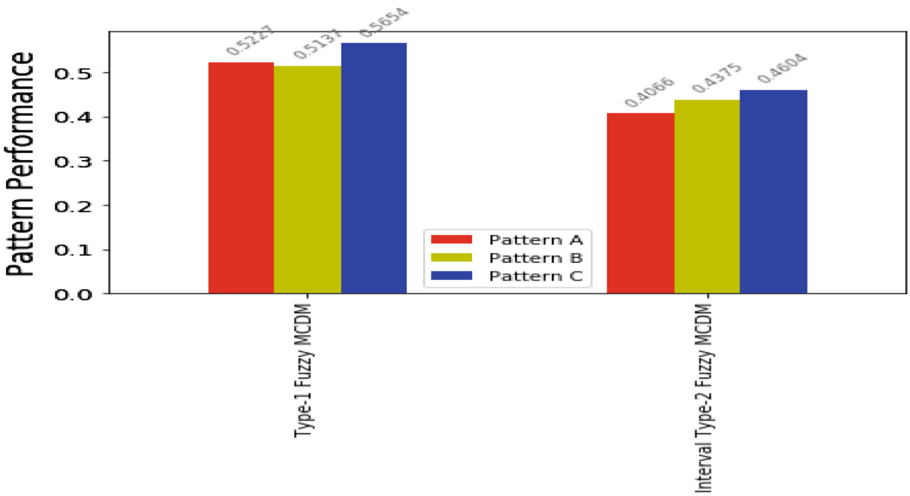

Fig. 3. Comparison of ranked patterns between the type-1 fuzzy MCDM and the proposed interval type-2 fuzzy MCDM approach

5 Results/Discussion

The performance metrics of patterns generated as rules are as follows: Accuracy (88.74%), Classification error (11.22%), Area Under Receiver Operating Characteristics curve (AUROC) (0.904). This shows that the model is reliable and can classify accurately. We extracted decision trees from the classifier and considered them as hidden patterns. The final values for the 3 patterns are shown in Table 7 using the Compensatory AND approach. These values are derived in terms of aggregated consideration of the 3 criteria defined i.e. (novelty, actionability and unexpectedness) which were then evaluated by the decision makers with respect to each pattern. Pattern C was the best with the overall value of 0.4604 followed by Pattern B with an overall value of 0.4375 while the least useful pattern was adjudged to be Pattern A with the overall value 0.4066. This gives an indication of the most critical patterns that decision makers can act on to drive business performance to the organization. Meanwhile, the overall weighted value of each criterion is depicted in Table 5 which shows the importance of each criterion in relation to the other. The Novelty of a pattern was adjudged to be the most critical feature in extracting useful insight from patterns mined with the weighted value of 0.4261 followed by Actionability with 0.2941 and Unexpectedness with 0.2798. Meanwhile, the type-1 fuzzy ranking of patterns showed a slight change between Pattern A and B as opposed to the interval type-2 as shown in Fig. 3. This could be as a result of both inter and intra uncertainties that cannot be accommodated sufficiently by the type-1 fuzzy. However, both confirmed pattern C as the most actionable (Tables 7 and 8).

6 Conclusions

Much of the research in the area of Knowledge Discovery in Databases (KDD) has focused on the development of more efficient and effective data mining algorithms. However, recently, issues relating to the usability of these techniques in extracting exploitable knowledge from databases has drawn significant attention. Therefore, this work proposed an interval type-2 fuzzy MCDM model for exploiting and ranking patterns in their order of subjective interestingness. Further research could be geared towards extending other variants of AHP methods with the interval type-2 fuzzy using the enhanced interval approach in order to be compared with our results.

References

1. Chen, F., Pan, D., Jiafu, W., Daqiang, Z., Athanasios, V., Xiaohui, R.: Data mining for the internet of things: literature review and challenges. Int. J. Distrib. Sens. Netw. (2015)
2. Amruta, L., Balachandra, k.: Performance evaluation of actionable knowledge discovery (AKD) framework under the decision making system. Int. J. Adv. Res. Comput. Sci. Eng. **3** (9) (2013)

3. Chiang, R.-D., Chang, M.-Y., Keh, H.-C., Chan, C.-H.: Mining unexpected patterns by decision trees with interestingness measures. In: 1st International Conference on Artificial Intelligence, Modelling and Simulation (AIMS), pp. 117–122. IEEE (2013). 978-1-4799-3251
4. Baykasoğlu, A., İlker, G.: Development of an interval type-2 fuzzy sets based hierarchical MADM model by combining DEMATEL and TOPSIS. Expert Syst. Appl. **70**, 37–51 (2017)
5. Mendel, J.M., Robert, I.J., Feilong, L.: Interval type-2 fuzzy logic systems made simple. IEEE Trans. Fuzzy Syst. **14**(6), 808–821 (2006)
6. Wu, D., Jerry, M.M., Simon, C.: Enhanced interval approach for encoding words into interval type-2 fuzzy sets and its convergence analysis. IEEE Trans. Fuzzy Syst. **20**(3), 499–513 (2012)
7. Chen, S., Li-Wei, L.: Fuzzy multiple attributes group decision-making based on the interval type-2 TOPSIS method. Expert Syst. Appl. **37**(4), 2790–2798 (2010)
8. Kahraman, C., Başar, Ö., İrem, U.S., Ebru, T.: Fuzzy analytic hierarchy process with interval type-2 fuzzy sets. Knowl.-Based Syst. **59**, 48–57 (2014)
9. Saaty, Thomas L.: The Analytic Hierarchy Process: Planning, Priority Setting, and Resource Allocation. MacGraw-Hill, New York International Book Company, New York (1980)
10. Zimmermann, H.J., Zysno, P.: Latent connectives in human decision making. Fuzzy Sets Syst. **4**(1), 37–51 (1980)
11. UCI Machine Repository Data. http://archive.ics.uci.edu/ml/dataset/Bank+Marketing