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A Study on the Rare Factors Exploration of Learning Effectiveness by Using Fuzzy Data Mining

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ABSTRACT
The phenomenon of low fertility has been negative impacted on the social structure of the educational environment in Taiwan. To increase the learning effectiveness of students became the most important issue for the Universities in Taiwan. Due to the subjective judgment of evaluators and the attributes of influenced factors are always fuzzy, it is not easy to measure the learning effectiveness by using the crisp values for the qualitative factors. In additional, the negative behaviors or the infrequent learning data (rare item sets) cannot easily excavate from educational database. Therefore, a systematic mining method is proposed here by combining fuzzy set theory with data mining technology to explore the key factors of learning effectiveness from the infrequent data. A case study implemented in this paper and showed that the proposed method can effectively find the important factors and valuable patterns from the survey data. The results of this paper can provide the important information for teachers to help students increase the learning effectiveness. Finally, the conclusions are addressed at the end of this paper.
Keywords: learning effectiveness, fuzzy data mining, association rules, rare item sets

INTRODUCTION

According to the report of the Ministry of the Interior Statistics Department in Taiwan, the fertility rate has dropped sharply in ten years. The fertility rate of the population has dropped to 8.53% in 2013 from 10.06% in 2003 (National Statistics, R.O.C., 2015a). The phenomenon of low fertility has been negative impacted on the social structure of the educational environment in Taiwan. Under this situation, the most of students can directly enter Universities after graduating from high school (National Statistics, R.O.C., 2015b). However, many students do not understand their interesting and the direction of future development in the learning process. The learning willingness of students always is low and reluctant to invest time to study even abandon their studies. Face the challenge and the restriction of educational resources, the most important issue for the colleges and Universities is to highlight the teaching performance to attract students.

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State of the literature

- In the educational field, the most learning behaviors of students are normal and easy to find out the pattern from the educational database.
- In fact, it needs more assistance for students who exhibit the negative behaviors. The rare behaviors patterns are sometimes helpful to teachers to identify the learning problems of students.
- Most of the association rule mining methods did not consider the ambiguity of data in the process of data pre-processing stage that cannot reflect the representative of data and human's cognition completely and truly.

Contribution of this paper to the literature

- Due to the subjective judgment of evaluators and the attributes of influenced factors are always fuzzy, the fuzzy set theory is applied in this paper to measure the learning effectiveness for the qualitative factors.
- The negative behaviors or the infrequent learning data (rare itemsets) cannot easily excavate from educational database. Therefore, a systematic mining method is proposed in this paper to explore the key factors of learning effectiveness from the infrequent data.
- A fuzzy association rules mining method is proposed by combining fuzzy set theory with rare data mining in this paper to explore the key factors of learning effectiveness and the relationships among factors.

Therefore, it is the most important issue for the Universities in Taiwan is to find the influenced factors of the learning effectiveness to improve the learn willingness of students.

Data mining techniques have been widely applied in the educational field in recent years. In the educational research field, data mining techniques can apply to dropout prediction of students (Kotsiantis, 2009), and learning performance prediction (Bhardwaj & Pal, 2012; Alfiani & Wulandari, 2015). Macfadyen and Dawson (2010) used data mining method to analyze the learners' archives, predict and build the learning effectiveness model. Data mining method can also apply to explore the data to describe the status of learners (Hu et al., 2014). Association rules is one of the most famous data mining methods, which explored the relationships among the data attributes (Agrawal et al, 1993; Han et al., 2001; Chen & Weng, 2009; Weng, 2011; Sowan et al, 2013; Shabana & Samuel, 2015; Palacios et al, 2015). An association rule mining is to generate all frequent itemsets and association rules that satisfy the minimum support and confidence values from the database. In the educational field, the most learning behaviors of students are normal and easy to find out the pattern from the educational database. However, some abnormal or negative behaviors of students are less frequent in the learning process. In fact, it needs more assistance for students who exhibit the negative behaviors. The rare behaviors patterns are sometimes helpful to teachers to identify the learning problems of students. Therefore, rare behaviors mining is an important issue for the educational research (Weng, 2011; Hoque et al., 2012; Tsang et al, 2013; Troiano & Scibelli, 2014; Bhatt & Patel, 2015a; Bhatt & Patel, 2015b; Goyal et

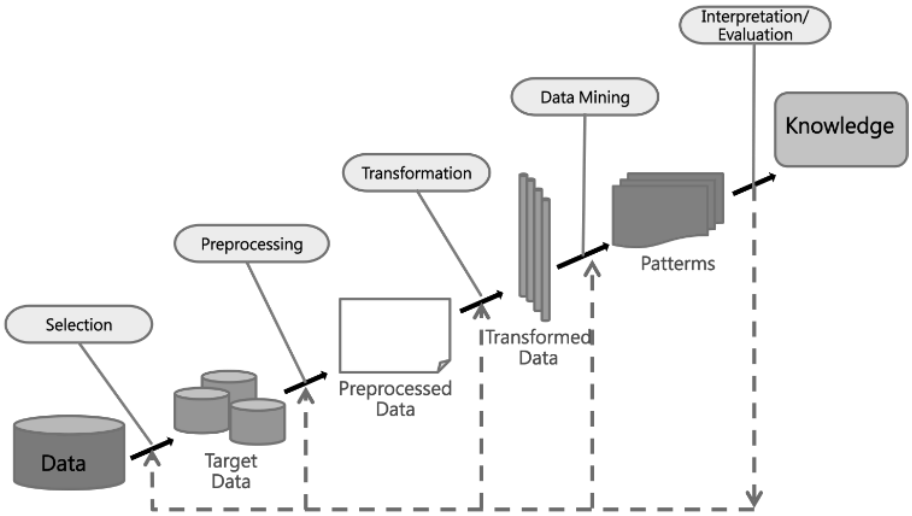

Figure 1. KDD Process (Fayyad et al., 1996)

al., 2015). However, most of the association rule mining methods did not consider the ambiguity of data in the process of data pre-processing stage that cannot reflect the representative of data and human's cognition completely and truly (Kuok et al., 1998; Kaya & Alhajj, 2003; Weng, 2011; Matthews et al, 2013; Wang et al, 2015). Therefore, converting the data into linguistic data by using fuzzy sets has become an important research direction for the data mining application (Ashish & Vikramkumar, 2010; Weng, 2011; Sowan et al., 2013; Jin et al., 2014; Arafah & Mukhlash, 2015; Palacios et al, 2015; Khatib et al, 2015).

In general, many quantitative and qualitative factors will influence the measurement of the learning effectiveness. Due to the subjective judgment of evaluators and the attributes of influenced factors are always fuzzy, it is not easy to measure the learning effectiveness by using the crisp values for the qualitative factors. Therefore, a fuzzy association rules mining method is proposed by combining fuzzy set theory with rare data mining in this paper to explore the key factors of learning effectiveness and the relationships among factors.

RELATED WORK

Data Mining

Data mining is considered as an important process to find new, valid, useful and interesting information from the database. Data mining techniques can be used for discovering knowledge in databases. Fayyad (1996) defined that data mining is the key step of knowledge discovery in database (KDD) process. The knowledge discovery process showed in Figure 1 (Fayyad et al., 1996).

Many researchers provided the different viewpoints to give the definition for data mining. Vlahos et al. (2004) considered that data mining is a computer-based information system (CBIS) to scan a huge database and discover knowledge. Han et al. (2011) noted that data mining is the process of dig out potentially useful and interesting feature from the database, data warehouse or other data storage devices. Pena-Ayala (2014) considered that data mining is used to identify the data patterns and find the hidden relationships among the factors by using the association rules. Therefore, the data mining technology can provide the valuable information to support decision-making for decision-makers. Data mining can also be defined as a technique to find interesting patterns or extracting useful information from the database (Alfiani, & Wulandari, 2015).

In general, data mining techniques can be divided into three categories such as "Association rules", "Classification and Prediction" and "Cluster Analysis" (Fayyad et al, 1996; Han and Kamber, 2006; Khan et al., 2008; Bhardwaj and Pal, 2012; Peña-Ayala, 2014; Alfiani and Wulandari, 2015). Association rules mainly extracted a series of relationships between variables or factors, and explored the implicit rules between the variables from the large dataset (Agrawal et al., 1993). Agrawal and Srikant (1994) used the association rules to find the relationship between purchasing behavior of consumer and product sales from the large transaction data. Association rules represented the relationships of factors by the rule. For example, if "A" is the occurrence then "B" also occurs, can be expressed as "A => B". Association rules commonly used to analyze the transaction behavior of consumer from the transaction database and apply the mining results to marketing and community research (Peña-Ayala, 2014; Siguenza-Guzman et al., 2015). The core concept of association rules is to represent a significant rule by using the "support (probability)" and "confidence (probability conditions)" values. The minimum support and confidence values are used to assess the value of information of an association rule. It can be defined as follows (Chien, & Hsu, 2014; Arafah, & Mukhlash, 2015):

(1) Support

Support value represents the probability of $P(X \cap Y)$ that it is the probability of “if item X occurs then item Y occurs”. It represents a ratio as:

$$Support\ (X \rightarrow Y) = P(X \cap Y) = \frac{n(X \cap Y)}{N} \quad (1)$$

where $n(X \cap Y)$ is that the number of items X and Y occurred simultaneously in the transaction database, N is the total number of transaction database.

(2) Confidence

Confidence value represents the conditional probability of $P(Y|X)$ that it represents the probability of item Y occurs when the item X has occurred. It can be computed as:

$$Confidence(X \rightarrow Y) = P(Y|X) = \frac{P(X \cap Y)}{P(X)} = \frac{n(X \cap Y)}{n(X)} \quad (2)$$

where $n(X)$ is that the number of items X occurred in the transaction database.

Apriori algorithm (Agrawal, & Srikant, 1994) is the first algorithm to discover the sequential patterns and widely applied in many areas such as business, sciences, advertising, marketing and medicine. The main steps of Apriori algorithm are:

(1) First, scan the transaction database to identify all *1-itemsets*. Then, set the minimum support value and determine the frequent *1-itemsets* that support values are larger than minimum support value. The frequent *1-itemsets* can note as L_1 and set $k = 1$.
(2) Let $k=k+1$. Generate the new candidate *k-itemsets* and denote the candidate *k-itemsets* by C_k after filtrating the parts of L_{k-1}.
(3) Calculate the support value of each itemsets in C_k and compare with the minimum support value. Then, remove ineligible itemset and collected the frequent *k-itemsets* as L_k.
(4) If all possible sets of items are calculated then go to step (5). On the contrary, it backs to the step (2).
(5) Calculate the confidence value of all frequent itemsets to find the significant association rules.

Learning Effectiveness

The definition of the "learning effectiveness" is that the learner changed after learning with knowledge, skills and attitudes (Piccoli et al., 2001). Boghikian-Whitby and Mortagy (2008) pointed out that the most significant factor of learning effectiveness is "learning outcomes" in the environment of higher education. The learning outcomes include pre-test, final exams and semester grade. Noesgaard and Ørngreen (2015) considered that "learning outcomes" is the popular definition of learning effectiveness for literature review and empirical research. They also suggested a quantitative measure to achieve the learning goals. In the "learning effectiveness" assessment, Hiltz and Wellman (1997) pointed out that learning achievement is the main item to measure the learning effectiveness. Lu et al. (2003) considered that the assessment of learning effectiveness can be measured based on the performance and satisfaction of student learning. Tsai and Chang (2007) pointed out that the learning effectiveness can usually be evaluated by using the tests and questionnaires in objective and subjective methodologies. Wang (2011) considered that the evaluation of learning effectiveness can refer the process of standardization of data collection. It can help educational organizations understand the experiences of teaching activities or provide their heritage. Chang and Chou (2015) used the four-level evaluation model (Kirkpatrick, & Kirkpatrick, 2009) to explore the learning effectiveness of e-learning courses through a structured questionnaire.

In summary, the concept of learning effectiveness is learners changed their knowledge, skills and attitudes after learning process. It also regarded as a measurement of reaching the learning goals of learners by teacher after teaching. Learning effectiveness of learners can be assessment two types such as "learning performance" and "learning perception". However, many quantitative and qualitative factors will influence the learning effectiveness measurement. It is not easy to measure the learning effectiveness because the subjective judgment of evaluators and the attributes of influenced factors are always fuzzy. In fact, find a set of rare items from infrequent education data that will be useful for teachers to find out which students need extra help in learning process. Therefore, a fuzzy association rules by combining fuzzy set theory with data mining proposed in this paper to explore the key factors of learning effectiveness from the infrequent data.

Fuzzy Set Theory

A fuzzy set can be defined mathematically by assigning to each possible element in the universe of discourse a value representing its grade of membership in the fuzzy set (Zadeh, 1965; Weng, 2011; Sowan et al., 2013; Khatib et al., 2015; Palacios et al., 2015). A fuzzy number $\tilde{A}$ is a fuzzy set whose membership function $\mu_{\tilde{A}}(x)$ satisfies the following conditions (Kaufmann, & Gupta, 1991; Klir and Yuan, 1995; Chen and Huang, 2006):

(i) $\mu_{\tilde{A}}(x)$ is piecewise continuous.

(ii) $\mu_{\tilde{A}}(x)$ is a convex fuzzy subset.

(iii) $\mu_{\tilde{A}}(x)$ is normality of a fuzzy subset.

(1) Positive Triangular Fuzzy Number

If a normal fuzzy sets $\tilde{A}$ = (a, b, c) is a Positive Triangular Fuzzy Number, then membership function $\mu_{\tilde{A}}(x)$ can be represented as follow (shown in **Figure 2**) (Klir et al., 1997):

$$\mu_{\tilde{A}}(x) = \begin{cases} \dfrac{x-a}{b-a}, \; a \le x \le b \\ \dfrac{x-c}{b-c}, \; b \le x \le c \\ 0, \; otherwise \end{cases} \tag{3}$$

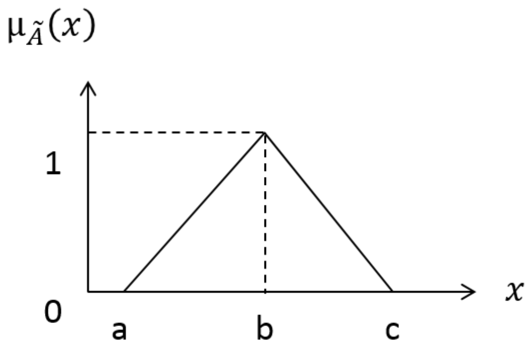

Figure 2. Positive Triangular Fuzzy Number

(2) Positive Trapezoidal Fuzzy Number

If a normal fuzzy sets $\tilde{n}$ = (a, b, c, d) is a Positive Trapezoidal Fuzzy Number, then membership function $\mu_{\tilde{n}}(x)$ can be represented as follow (shown in **Figure 3**) (Chen et al., 2006):

$$\mu_{\tilde{n}}(x) = \begin{cases} 0,\ x < a \\ \dfrac{x-a}{b-a},\ a \le x \le b \\ 1,\ b \le x \le c \\ \dfrac{x-d}{c-d},\ c \le x \le d \\ 0,\ x > d \end{cases} \tag{4}$$

where a > 0 and a ≤ b ≤ c ≤ d.

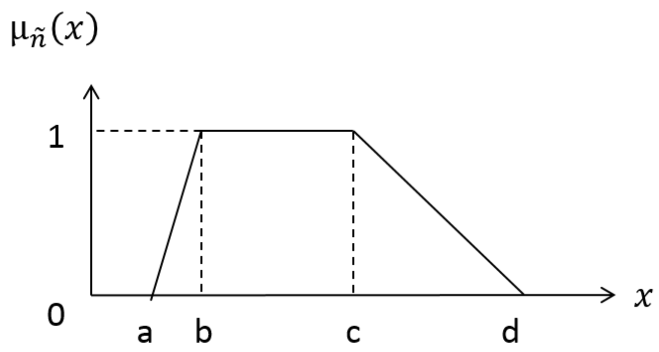

Figure 3. Positive Trapezoidal Fuzzy Number

Suppose there are two fuzzy sets $\tilde{A}$ and $\tilde{B}$, its membership function are $\mu_{\tilde{A}}(x)$ and $\mu_{\tilde{B}}(x)$ in U_x. Then the intersection and union operations of the two fuzzy sets are as follows (Zadeh, 1965; Hong et al., 1999; Weng, 2011; Palacios et al., 2015):

(1) Intersection

$$\mu_{\tilde{A}\cap\tilde{B}}(x) = \min_x\{\mu_{\tilde{A}}(x),\ \mu_{\tilde{B}}(x)\},\ \forall x \in U_x \tag{5}$$

(2) Union

$$\mu_{\tilde{A}\cup\tilde{B}}(x) = \max_x\{\mu_{\tilde{A}}(x),\ \mu_{\tilde{B}}(x)\},\ \forall x \in U_x \tag{6}$$

Fuzzy Apriori Rare Itemset Mining

Most of the educational records are normal behaviors of students that can easy to find and represent by the frequent patterns. However, the more specific or negative behaviors are not easy to be excavated (Weng, 2011). In fact, students who have specific negative behaviors may need more support and help to learn. Educators can try to find infrequent rare itemsets from the educational data to identify the characteristics of students. It is helpful for teachers to provide students learning with extra help. Weng (2011) found the rare itemsets from student achievement data, and then found the related behaviors of students for teachers to identify the learning problem of students. Fuzzy Apriori Rare Itemset Mining algorithms (FARIM) is proposed by Weng (2011) for mining the specific fuzzy rare itemsets from the quantitative data to generate fuzzy association rules. The main process of FARIM algorithm illustrated as **Figure 4**. The relevant symbols in FARIM are defined as follows:

(1) Set $\boldsymbol{IT} = \{\boldsymbol{it_1}, \boldsymbol{it_2}, \dots, \boldsymbol{it_m}\}$, an ***s-item***=$(\boldsymbol{it_i},\ \boldsymbol{s_i})$. An *r-item* can be a linguistic *s-item*, use $\boldsymbol{b_i} = (\boldsymbol{ic_i}, \boldsymbol{f_i})$ to denote an r-item. All *r-items* $\boldsymbol{B} = \{(\boldsymbol{ic_1}, \boldsymbol{f_1}), (\boldsymbol{ic_2}, \boldsymbol{f_2}), \dots, (\boldsymbol{ic_n}, \boldsymbol{f_n})\}$.

(2) A fuzzy set *F* is characterized by a membership function $\boldsymbol{m_F}(\boldsymbol{x})$, which maps *x* to a membership degree in interval [0, 1].

(3) Assume that we have a number *s-item* $\boldsymbol{a_i} = (\boldsymbol{it_i}, \boldsymbol{s_i})$, a linguistic *r-item* $\boldsymbol{b_j} = (\boldsymbol{ic_j}, \boldsymbol{f_j})$, and a membership function $(\boldsymbol{FS_{f_j}})$. Then, $\boldsymbol{sup}(\boldsymbol{a_i}, \boldsymbol{b_j})$ and $\boldsymbol{rnk}(\boldsymbol{a_i}, \boldsymbol{b_j})$ can be computed as follows:

$$sup(a_i,\ b_j) = \begin{cases} FS_{f_j}(s_i),\ if\ it_i = ic_j \\ \quad 0,\ otherwise \end{cases} \tag{7}$$

$$rank(a_i,\ b_j) = \begin{cases} \dfrac{s_i - s_{min}}{s_{max} - s_{min}},\ if\ it_i = ic_j \\ \quad 0,\ otherwise \end{cases} \tag{8}$$

(4) A rule *r-item* can be a linguistic *r-item*. We use $\boldsymbol{b_i} = (\boldsymbol{ic_i}, \boldsymbol{f_i})$ to denote a rule *r-item*, and $\boldsymbol{B} = \{(\boldsymbol{ic_1}, \boldsymbol{f_1}), (\boldsymbol{ic_2}, \boldsymbol{f_2}), \dots, (\boldsymbol{ic_n}, \boldsymbol{f_n})\}$ to denote a rule *r-itemset.*

(5) Let an *s-itemset* be a set of *s-items*. Assume that we have an *s-itemset*$\boldsymbol{A} = \{(\boldsymbol{it_1},\ \boldsymbol{s_1}),\ (\boldsymbol{it_2},\ \boldsymbol{s_2}),\ \dots,\ (\boldsymbol{it_m},\ \boldsymbol{s_m})\}$, where $\boldsymbol{a_i} = (\boldsymbol{it_i}, \boldsymbol{s_i})$. Assume that we have a rule *r-itemset* $\boldsymbol{B} = \{(\boldsymbol{ic_1}, \boldsymbol{f_1}), (\boldsymbol{ic_2}, \boldsymbol{f_2}), \dots, (\boldsymbol{ic_n}, \boldsymbol{f_n})\}$, where $\boldsymbol{b_j} = (\boldsymbol{ic_j}, \boldsymbol{f_j})$. If we can find $a_{i_1} \le a_{i_2} \le \cdots \le a_{i_n}$ in *A*, such that $sup(a_{ij}, b_j) > 0$, then *sup(A, B)* and *rnk(A, B)* can be computed as follows:

$$sup(A,\ B) = Min_{j=1}^{n} sup(a_{ij},\ b_j) \tag{9}$$

$$rnk(A,\ B) = Min_{j=1}^{n} rnk(a_{ij},\ b_j) \tag{10}$$

(6) Assume that we have a database *D*, one of the sid-th transaction in *D* can be represented as:

s-itemset $A_{sid} = \{(it_1,\ s_1),\ (it_2,\ s_2),\ \dots,\ (it_m,\ s_m)\}$

r-itemset $B = \{(ic_1,\ f_1),\ (ic_2,\ f_2),\ \dots,\ (ic_n,\ f_n)\}$

Then, the support and rank of B occurred in *D*, $sup_D(B)$ and $rnk_D(B)$, can be computed as follows:

$$sup_D(B) = \frac{\left(\sum_{sid=1}^{|D|} sup(A_{sid},\ B)\right)}{|D|} \tag{11}$$

$$rnk_D(B) = \frac{\left(\sum_{sid=1}^{|D_B|} rnk(A_{sid},\ B)\right)}{|D|} \tag{12}$$

where $|D|$is the total number of transactions in database D, and $|D_B|$is the subset of transactions in database D with itemset B.

(7) Given a user-specified threshold value σ_s, a rule *r-itemset* B is rare if $sup_D(B)$ is no larger than σ_s. Let B be a rare rule r-itemset, where $B = X \cup Y \text{ and } X \cap Y = \emptyset$. Then, the confidence of rule $X \Longrightarrow Y$, denoted as $conf(X \Rightarrow Y)$ and computed as follows:

$$conf(X \Rightarrow Y) = \frac{sup_D(B)}{sup_D(X)} \tag{13}$$

(8) Finally, given a confidence threshold value σ_c, if $\boldsymbol{conf}(\boldsymbol{X} \Rightarrow \boldsymbol{Y}) \geq \boldsymbol{\sigma_c}$, then $\boldsymbol{X} \Longrightarrow \boldsymbol{Y}$ in D.

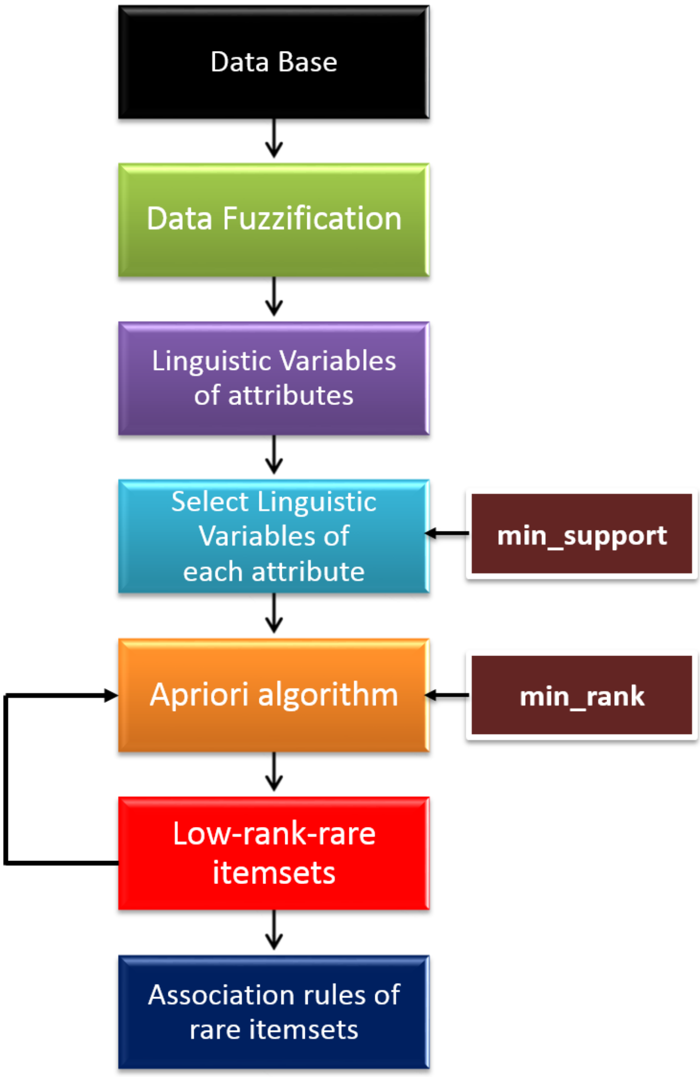

Figure 4. FARIM Process

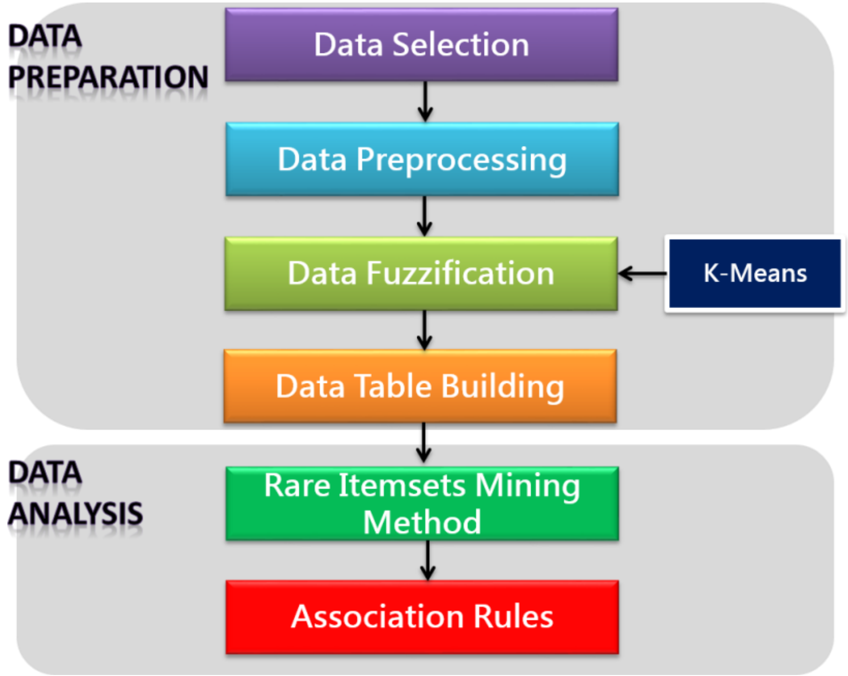

Figure 5. Research process

DATA MINING METHOD WITH RARE ITEMSETS

Research Process

The research process of this paper can be divided into two stages such as "data preparation" and "data analysis". The flow chart of research process is shown in Figure 5. The main steps in the data preparation are "data selection", "data preprocessing", "data fuzzification" and "data table building". In the stage of the data analysis can be divided into mining rare itemsets and identify association rules of learning effectiveness.

Data Preprocessing

The users or experts in many studies of the fuzzy data mining often determine the membership functions of data fuzzification. However, it is not easy to classify the data objectively (Weng, 2011; Krömer et al., 2013; Arafah & Mukhlash, 2015; Palacios et al., 2015). Therefore, the cluster analysis of machine learning technique is applied to produce a center of membership functions. In this study, the data of each attribute can be divided into three groups, and linguistic variables are represented as "poor", "med" and "good". The K-Means is a cluster analysis method (Alfiani, & Wulandari, 2015). In this paper, K-means is applied to determine the central point of each linguistic variable as "C_{poor}", "C_{med}" and "C_{good}". Membership functions of linguistic variables are shown as Figure 6. The membership functions of linguistic variables are shown as equations (14), (15) and (16).

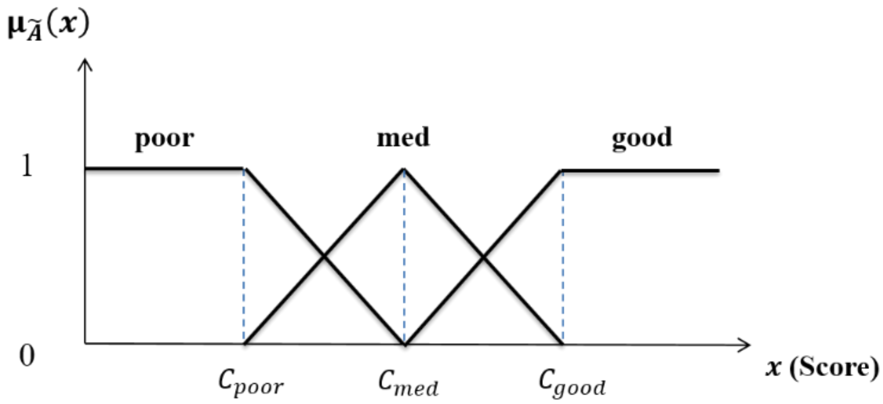

Figure 6. Membership functions of linguistic variables

$$\mu_{poor}(x) = \begin{cases} 1, \ x \leq C_{poor} \\ \dfrac{x - C_{med}}{C_{poor} - C_{med}}, \ C_{poor} \leq x \leq C_{med} \\ 0, \ x \geq C_{med} \end{cases} \tag{14}$$

$$\mu_{med}(x) = \begin{cases} \dfrac{x - C_{poor}}{C_{med} - C_{poor}}, \ C_{poor} \leq x \leq C_{med} \\ \dfrac{x - C_{good}}{C_{med} - C_{good}}, \ C_{med} \leq x \leq C_{good} \\ 0, \ otherwise \end{cases} \tag{15}$$

$$\mu_{good}(x) = \begin{cases} 1, \ x \geq C_{good} \\ \dfrac{x - C_{med}}{C_{good} - C_{med}}, \ C_{med} \leq x \leq C_{good} \\ 0, \ x \leq C_{med} \end{cases} \tag{16}$$

EXAMPLE

Data Preparation

A case study implemented in this paper. The collection data are the scores of four courses for the students of Department of Information Management in National United University, Taiwan. The names of four courses are "Statistics", "Management Science", "Data structures" and "Database management system". The "grade point average" (GPA) is objective variables of this study. The maximum score of each course is 120. There are 118 students in this case study and 103 valid data are used to mining the associate rules. Transfer the data of each course into three linguistic variables such as “Poor”, “Med”, and “Good”. The K-Means method applied to determine the center values of membership functions of linguistic variables. The result of data translation can be shown as **Table 1**.

Table 1. Quantitative data translation

Attribute Code	Average	Standard deviation	Linguistic variables		
			Poor (Center Value)	Med (Center Value)	Good (Center Value)
STA	87.73	14.72	Poor (45)	Med (81)	Good (97)
MS	80.51	22.48	Poor (54)	Med (84)	Good (108)
DS	38.97	11.58	Poor (21)	Med (37)	Good (54)
DBMS	68.47	22.53	Poor (37)	Med (67)	Good (94)
GPA	72.12	13.97	Poor (54)	Med (73)	Good (87)

Data Analysis

There are 103 valid data are used to mining the associate rules of rare itemsets in case study. The scores of students are shown as **Table 2**. The "grade point average" regarded as the objective variable. Assume the min_support is set to 0.22, the lowest ranking value (rnk) is set to 0.22, and the min_confidence is set to 0.8. The steps of fuzzy apriori rare mining method can be illustrated as follows.

(1) According to the **Table 2**, the data can be converted into linguistic variables to calculate the support (sup) and ranking (rnk) values as shown in **Table 3**.

(2) Calculate each support value of r-item and check it. If it is less than the minimum support then put this item into rare itemsets. Check all rnk values of rare itemsets and put these items into the "low-rank-rare itemsets" which the rnk values are less than the minimum rnk as shown in **Table 4**.

(3) Based on results of **Table 4**, determine a maximum sub-itemset sequential in accordance with the target variable, "Grade Point Average (GPA)". Calculate the values of sup and rnk, then reserved the items that the rnk values are less than the minimum rnk. The results are shown in **Table 5**.

(4) According to the results of **Table 5**, the highest itemset is four-items of the low-rare-rank itemsets for this study. According to the confidence threshold value, there are two association rules as shown in **Table 6**.

This study applied fuzzy data mining techniques to mining fuzzy association rules of rare itemsets for the learning effectiveness of students. According to the **Table 6**, if the scores of statistics, data structures and database management system all are poor, then "Grade Point Average" is also poor. If the scores of management science is good but data structures and database management systems both are poor, then "Grade Point Average" is also poor. Therefore, we can find that "Data Structures" and "Database Management Systems" are main courses to influence the "Grade Point Average" of students. Based on the results of case study, it shows that the proposed method can effectively find the important factors and association rules for the rare itemsets. The results of this paper are meaningful for teachers to provide more assistance to students. In other words, teachers should pay more attentions to students who have both poor scores of "Data Structures" and "Database Management Systems" to increase their learning effectiveness.

Table 2. The scores data of students

NO.	STA	MS	DS	DBMS	GPA
1	60	20	0	50	42
2	79	85	44	85	73
3	88	95	52	72	79
…	…	…	…	…	…
…	…	…	…	…	…
…	…	…	…	…	…
101	91	62	24	60	62
102	75	38	15	20	38
103	71	62	41	70	62

Table 3. Sup and rnk values of attributes

Case NO.	STA			MS			DS			DBMS			GPA		
	r-item	Sup	Rnk	r-item	Sup	Rnk	r-item	Sup	Rnk	r-item	Sup	Rnk	r-item	Sup	Rnk
1	Poor	0.58	0.52	Poor	1.00	0.17	Poor	1.00	0.00	Poor	0.57	0.37	Poor	1.00	0.21
2	Med	0.94	0.73	Med	0.96	0.71	Med	0.59	0.68	Good	0.67	0.74	Med	1.00	0.65
3	Med	0.56	0.83	Med	0.54	0.79	Good	0.88	0.80	Med	0.81	0.60	Med	0.57	0.73
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
101	Good	0.63	0.87	Poor	0.73	0.52	Poor	0.81	0.37	Med	0.77	0.47	Poor	0.58	0.49
102	Med	0.83	0.69	Poor	1.00	0.32	Poor	1.00	0.23	Poor	1.00	0.05	Poor	1.00	0.15
103	Med	0.72	0.64	Poor	0.73	0.52	Med	0.76	0.63	Med	0.89	0.58	Poor	0.58	0.49

Table 4. Low-rank-rare 1-itemsets

Low-rank-rare 1-itemsets	Sup	Rnk
STA_Poor	0.05	0.02
MS_Good	0.19	0.20
DS_Poor	0.11	0.05
DS_Good	0.22	0.21
DBMS_Poor	0.19	0.05
GPA_Poor	0.21	0.10

COMPARATIVE ANALYSIS

In this study, the K-means clustering method applied to determine the center value of the membership function of each linguistic variable. It can determine the center value of the membership function reasonably based on the spread situations of data set. We implemented

Table 5. Low-rank-rare x-itemsets

***Low-rank-rare* 2-Itemsets**	**Sup**	**Rnk**
STA_Poor ∩ GPA_Poor	0.04	0.02
MS_Good ∩ GPA_Poor	0.01	0.01
DS_Poor ∩ GPA_Poor	0.07	0.04
DS_Good ∩ GPA_Poor	0.01	0.01
DBMS_Poor ∩ GPA_Poor	0.12	0.06
***Low-rank-rare* 3-Itemsets**	**Sup**	**Rnk**
STA_Poor ∩ DS_Poor ∩ GPA_Poor	0.01	0.01
STA_Poor ∩ DS_Good ∩ GPA_Poor	0.03	0.02
STA_Poor ∩ DBMS_Poor ∩ GPA_Poor	0.01	0.01
MS_Good ∩ DS_Poor ∩ GPA_Poor	0.01	0.01
MS_Good ∩ DS_Good ∩ GPA_Poor	0.04	0.02
MS_Good ∩ DBMS_Poor ∩ GPA_Poor	0.01	0.01
Low-rank-rare 4-Itemsets	**Sup**	**Rnk**
STA_Poor ∩ DS_Poor ∩ DBMS_Poor ∩ GPA_Poor	0.01	0.01
MS_Good ∩ DS_Poor ∩ DBMS_Poor ∩ GPA_Poor	0.01	0.01

Table 6. Association rules of rare itemsets

Association Rules	**Con.**
If Scores of Statistics, Data Structures and Database Management Systems are all Poor, then Grade Point Average is Poor.	1.00
If Scores of Management Science is Good, but Scores of Data Structures and Database Management Systems both are Poor, then Grade Point Average is Poor.	1.00

a comparative study between proposed method and other clustering methods. The second and third methods used the average ($\bar{x}$) and standard deviation (s) of data to determine the center values of the membership functions. In the second method, the center values of the membership functions are $\bar{x}-0.5s$, $\bar{x}$, and $\bar{x}+0.5s$. In the third method, the center values of the membership functions are $\bar{x}-s$, $\bar{x}$, and $\bar{x}+s$. The fourth method assigned the center values of the membership functions by the researcher. The assigned results in this case study shown in **Table 7**. The comparison results of the four clustering methods as shown in **Table 8**. According the **Table 8**, the association rules are not consistent based on the methods II and III. The reason is that the mining results will be influenced by the data spread. In additional, the confidence of the association rule is lower by using the method IV. It indicates that the randomly assigned by the researcher is not good method to determine the center values of the membership functions. Therefore, the proposed method of this paper is a better way for mining the rules to explain the factors of learning effectiveness.

Table 7. Assigned the cluster center by the researcher

Attribute Code	Linguistic variables		
	Poor (Center Value)	Med (Center Value)	Good (Center Value)
STA	Poor (60)	Med (88)	Good (95)
MS	Poor (60)	Med (81)	Good (95)
DS	Poor (25)	Med (40)	Good (60)
DBMS	Poor (55)	Med (69)	Good (80)
GPA	Poor (60)	Med (73)	Good (90)

Table 8. Comparison results

Method	Clustering	Results
I. (Proposed Method)	K-means	STA_Poor∩DS_Poor∩DBMS_Poor → GPA_Poor (Con. = 1.00) MS_Good∩DS_Poor∩DBMS_Poor → GPA_Poor (Con. = 1.00)
II.	Average and 0.5 times standard deviation	STA_Med∩MS_Med∩DS_Med → GPA_Med (Con. = 1.00)
III.	Average and 1.0 times standard deviation	No Association Rules.
IV.	Assign by the researcher	DS_Good∩DBMS_Med→GPA_Good (Con. = 0.61)

CONCLUSIONS

The issue of big data has received attentions for many fields in recent years. Many researchers also have invested time to apply data mining technology in educational field. However, most of association rule mining techniques are used to find the frequent patterns from the database, but some low frequency factors with important information has been ignored in the data mining process. In fact, many quantitative and qualitative factors should be considered to measure the learning effectiveness. Because the subjective judgment of evaluators and the attributes of influenced factors are always fuzzy, it is not easy to measure the learning effectiveness by using the crisp values. Therefore, a fuzzy mining method by combining fuzzy set theory with data mining is proposed here to explore the key factors of rare attributes for the learning effectiveness of students.

Based on the results of case study, it shows that the proposed method can effectively find the important factors and association rules for the rare attributes of learning effectiveness. The results of this paper can provide the important information for teachers to help students increase the learning effectiveness.

However, the data collected only from the undergraduate students of the National University Department of Information Management in Taiwan. The results of case study cannot extend easily to explain the learning situation of students for other Universities. In additional, some important and interesting factors may not consider in data collection process. In the future, the fuzzy C-means or other data classification methods can use to determine the centers of the membership functions of each attribute. More data and the attributes can collect to explore the relationships between influenced factors and their impact on the learning effectiveness.

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