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

Chen-Tung Chen
National United University, TAIWAN

Kai-Yi Chang
National United University, TAIWAN

Received 28 May 2016 • Revised 9 August 2016 • Accepted 8 November 2016

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 addition, 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.
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
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 & Alhaji, 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:

\[
\text{Support} \ (X \rightarrow Y) = \frac{n(X \cap Y)}{N}
\]

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 \( P(Y \mid X) \) that it represents
the probability of item Y occurs when the item X has occurred. It can be computed as:

\[
\text{Confidence}(X \rightarrow Y) = \frac{P(X \cap Y)}{P(X)} = \frac{n(X \cap Y)}{n(X)}
\]

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):

   \[
   \mu_{\tilde{A}}(x) = \begin{cases} 
   \frac{x-a}{b-a}, & a \leq x \leq b \\
   \frac{x-c}{b-c}, & b \leq x \leq c \\
   0, & \text{otherwise}
   \end{cases}
   \]

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):

\[\text{Figure 2. Positive Triangular Fuzzy Number}\]

\[\text{Figure 3. Positive Trapezoidal Fuzzy Number}\]
Figure 3. Positive Trapezoidal Fuzzy Number

\[
\mu_{\tilde{A}}(x) = \begin{cases} 
0, & x < a \\
\frac{x - a}{b - a}, & a \leq x \leq b \\
1, & b \leq x \leq c \\
\frac{x - d}{c - d}, & c \leq x \leq d \\
0, & x > d 
\end{cases}
\]  

(4)

where \(a > 0\) and \(a \leq b \leq c \leq d\).

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
\[
\mu_{\tilde{A} \cap \tilde{B}}(x) = \min_{x} \{\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)\}, \forall x \in U_x
\]

(5)

2. Union
\[
\mu_{\tilde{A} \cup \tilde{B}}(x) = \max_{x} \{\mu_{\tilde{A}}(x), \mu_{\tilde{B}}(x)\}, \forall x \in U_x
\]

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

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

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

\[
\text{sup}(a_i, b_j) = \begin{cases} 
FS_{f_j}(s_i), & \text{if } it_i = ic_j \\
0, & \text{otherwise}
\end{cases}
\]

\[
\text{rnk}(a_i, b_j) = \begin{cases} 
\frac{s_i - s_{\text{min}}}{s_{\text{max}} - s_{\text{min}}}, & \text{if } it_i = ic_j \\
0, & \text{otherwise}
\end{cases}
\]

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

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

\[
\text{sup}(A, B) = \min_{j=1}^{n} \text{sup}(a_{i_j}, b_j)
\]

\[
\text{rnk}(A, B) = \min_{j=1}^{n} \text{rnk}(a_{i_j}, b_j)
\]

6. Assume that we have a database \( D \), one of the \( \text{id} \)-th transaction in \( D \) can be represented as:

\( s \)-itemset \( A_{\text{id}} = \{(it_1, s_1), (it_2, s_2), \ldots, (it_m, s_m)\} \)

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

Then, the support and rank of \( B \) occurred in \( D \), \( \text{sup}_D(B) \) and \( \text{rnk}_D(B) \), can be computed as follows:

\[
\text{sup}_D(B) = \frac{\sum_{\text{id}=1}^{|D|} \text{sup}(A_{\text{id}}, B)}{|D|}
\]

\[
\text{rnk}_D(B) = \frac{\sum_{\text{id}=1}^{|D|} \text{rnk}(A_{\text{id}}, B)}{|D|}
\]
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 \( \sigma_s \), a rule \( r \)-itemset \( B \) is rare if \( sup_D(B) \) is no larger than \( \sigma_s \). Let \( B \) be a rare rule \( r \)-itemset, where \( B = X \cup Y \) and \( X \cap Y = \emptyset \). Then, the confidence of rule \( X \Rightarrow Y \), denoted as \( conf(X \Rightarrow Y) \) and computed as follows:

\[
conf(X \Rightarrow Y) = \frac{sup_D(B)}{sup_D(X)}
\]  

(13)

(8) Finally, given a confidence threshold value \( \sigma_c \), if \( conf(X \Rightarrow Y) \geq \sigma_c \), then \( X \Rightarrow Y \) in \( D \).

**Figure 4.** FARIM 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 equations (14), (15) and (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.

![Membership functions of linguistic variables]

Figure 6. Membership functions of linguistic variables

\[
\mu_{\text{poor}}(x) = \begin{cases} 
1, & x \leq C_{\text{poor}} \\
\frac{x - C_{\text{med}}}{C_{\text{poor}} - C_{\text{med}}}, & C_{\text{poor}} \leq x \leq C_{\text{med}} \\
0, & x \geq C_{\text{med}}
\end{cases} 
\] (14)

\[
\mu_{\text{med}}(x) = \begin{cases} 
\frac{x - C_{\text{poor}}}{C_{\text{med}} - C_{\text{poor}}}, & C_{\text{poor}} \leq x \leq C_{\text{med}} \\
\frac{x - C_{\text{good}}}{C_{\text{med}} - C_{\text{good}}}, & C_{\text{med}} \leq x \leq C_{\text{good}} \\
0, & \text{otherwise}
\end{cases} 
\] (15)

\[
\mu_{\text{good}}(x) = \begin{cases} 
1, & x \geq C_{\text{good}} \\
\frac{x - C_{\text{med}}}{C_{\text{good}} - C_{\text{med}}}, & C_{\text{med}} \leq x \leq C_{\text{good}} \\
0, & x \leq C_{\text{med}}
\end{cases} 
\] (16)
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  |

**Table 3.** Sup and rnk values of attributes

| Case NO. | r-item Sup | r-item Rnk | STA | r-item Sup | r-item Rnk | MS | r-item Sup | r-item Rnk | DS | r-item Sup | r-item Rnk | DBMS | r-item Sup | r-item Rnk | GPA |
|----------|------------|------------|-----|------------|------------|----|------------|------------|----|------------|------------|------|------------|------------|-----|
| 1        | Poor       | 0.58       | 0.52| Poor       | 0.05       | Poor| 0.17       | 0.02       | Poor| 0.00       | 0.37       | Poor| 0.57       | 0.37       | 0.21|
| 2        | Med        | 0.94       | 0.73| Med        | 0.96       | 0.71| Med        | 0.59       | Good| 0.68       | 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|

**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|
| DBMS Poor                 | 0.22| 0.21|
| GPA Poor                  | 0.19| 0.05|

**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
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 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 |
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 technique 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

**Table 7.** Assigned the cluster center by the researcher

| Attribute Code | 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
attributes can collect to explore the relationships between influenced factors and their impact on the learning effectiveness.

ACKNOWLEDGMENT

This work is partially supported by the Ministry of Science and Technology of Taiwan under grant No. MOST 103-2410-H-239-008-MY2.

REFERENCES

National Statistics, R.O.C. (Taiwan) (2015a). Births, Birth Rate, Deaths, Death Rate. (2015, September 30). Retrieved from http://sowf.moi.gov.tw/stat/month/m1-02.ods

National Statistics, R.O.C. (Taiwan) (2015b). Education at all levels of school-age population rate. (2015, September 30). Retrieved from http://statdb.dgbas.gov.tw/pxweb/Dialog/varval.asp?ma=ER0102A1A&ti=%A6U%AF%C5%B1%D0%A8%BE%C7%C4%D6%A4H%A4%A6b%BE%C7%B2v%A6~&path=../PXfile/Education/&lang=9&strList=L

Agrawal, R., Imielinski, T., & Swami, A. (1993). Mining Association Rules between Sets of Items in Large Databases. Proceedings of the 1993 ACM SIGMOD Conference on Management of Data, 207-216.

Agrawal, R., & Srikant, R. (1994). Fast algorithms for mining association rules. Proc. 20th int. conf. very large data bases, 1215, 487-499.

Alfiani, A. P., & Wulandari, F. A. (2015). Mapping Student's Performance Based on Data Mining Approach (A Case Study). Agriculture and Agricultural Science Procedia, 3, 173-177.

Arafah, A. A., & Mukhlash, I. (2015). The Application of Fuzzy Association Rule on Comovement Analyze of Indonesian Stock Price. Procedia Computer Science, 59, 235-243.

Ashish, M., & Vikramkumar, P. (2010). FPrep: Fuzzy clustering driven efficient automated preprocessing for fuzzy association rule mining. Proceedings of IEEE international conference on Fuzzy systems, 1-8.

Bhardwaj, B. K., & Pal, S. (2012). Data Mining: A prediction for performance improvement using classification. International Journal of Computer Science and Information Security, 9(4), 136-140.

Bhatt, U. Y., & Patel, P. A. (2015a). Mining Interesting Rare Items with Maximum Constraint Model Based on Tree Structure. Fifth International Conference on Communication Systems and Network Technologies, 1065-1070.

Bhatt, U. Y., & Patel, P. A. (2015b). A Novel Approach for Finding Rare Items Based on Multiple Minimum Support Framework. Procedia Computer Science, 57, 1088-1095.

Boghikian-Whitby, S., & Mortagy, Y. (2008). The effect of student background in e-learning–longitudinal study. Issues in Informing Science and Information Technology, 5, 107-126.

Chang, N. C., & Chou, T. (2015). Evaluating the Learning Effectiveness of the Information Law Course in a Blended Learning Environment Based on the Kirkpatrick Model. Journal of Educational Media & Library Sciences, 52(4), 1-29.

Chen, C.T., Huang, S.F. (2006) Order-fulfillment ability analysis in the supply-chain system with fuzzy operation times. International Journal of Production Economics, 101, 185-193.

Chen, C. T., Lin, C. T., & Huang, S. F. (2006). A fuzzy approach for supplier evaluation and selection in supply chain management. International journal of production economics, 102(2), 289-301.
Chen, Y. L., & Weng, C. H. (2009). Mining fuzzy association rules from questionnaire data. *Knowledge-Based Systems, 22*(1), 46-56.

Chien, C. F., & Hsu, C. Y. (2014). Data Mining & Big Data Analytics. New Taipei: Future Career Publishing Corporation.

Fayyad, U. M. (1996). Data mining and knowledge discovery: Making sense out of data. *IEEE Intelligent Systems, 11*(5), 20-25.

Fayyad, U. M., Piatetsky-Shapiro, G., & Smyth, P. (1996). From data mining to knowledge discovery in databases. *AI magazine, 17*(3), 37-54.

Goyal, V., Dawar, S., & Sureka, A. (2015). High Utility Rare Itemset Mining over Transaction Databases. *Lecture Notes in Computer Science, 8999*, 27-40.

Han, J., & Kamber, W. (2001). Data Mining: Concepts and Techniques. San Francisco: Morgan Kaufman.

Han, J., & Kamber, M. (2006). Data Mining: Concepts and Techniques (2nd ed.). San Francisco: Morgan Kaufman.

Han, J., Kamber, M., & Pei, J. (2011). Data Mining: Concepts and Techniques (3rd ed.). San Francisco: Morgan Kaufman.

Hiltz, S. R., & Wellman, B. (1997). Asynchronous *Learning Networks as a Virtual Classroom*. *Communications of the ACM, 40*(9), 44-49.

Hong, T. P., Kuo, C. S., & Chi, S. C. (1999). Mining association rules from quantitative data. *Intelligent Data Analysis, 3*(5), 363-376.

Hoque, N., Nath, B., & Bhattacharyya, D. K. (2012). A new approach on rare association rule mining. *International Journal of Computer Applications, 53*(3), 1-6.

Hu, Y. H., Lo, C. L., & Shih, S. P. (2014). Developing early warning systems to predict students’ online learning performance. *Computers in Human Behavior, 36*, 469-478.

Jin, C., Li, F., & Li, Y. (2014). A generalized fuzzy ID3 algorithm using generalized information entropy. *Knowledge-Based Systems, 64*, 13-21.

Kaufmann, A., & Gupta, M. M. (1991). Introduction to Fuzzy Arithmetic: Theory and Applications, International Thomson Computer Press. New York: VanNostrand Reinhold.

Kaya, M., & Alhajj, R. (2003). Facilitating fuzzy association rules mining by using multi-objective genetic algorithms for automated clustering. *Proceedings of the third IEEE international conference on data mining*, 561-564.

Khan, M. S., Muyeba, M., & Coenen, F. (2008). A weighted utility framework for mining association rules. *Computer Modeling and Simulation, 87*-92.

Khatib, E. J., Barco, R., Gómez-Andrades, A., Muñoz, P., & Serrano, I. (2015). Data mining for fuzzy diagnosis systems in LTE networks. *Expert Systems with Applications, 42*(21), 7549-7559.

Kirkpatrick, D. L., & Kirkpatrick, J. D. (2009). Evaluating Training Programs: The Four Levels. San Francisco: Berrett-Koehler.

Klir, G.J., Yuan, B. (1995) Fuzzy Sets and Fuzzy Logic, International Editions, Prentice-Hall.

Kotsiantis, S. (2009). Educational data mining: a case study for predicting dropout-prone students. *International Journal of Knowledge Engineering and Soft Data Paradigms, 1*(2), 101-111.
Krömer, P., Owais, S., Platoš, J., & Snášel, V. (2013). Towards new directions of data mining by evolutionary fuzzy rules and symbolic regression. *Computers & Mathematics with Applications, 66*(2), 190-200.

Kuok, C. M., Fu, A., & Wong, M. H. (1998). Mining fuzzy association rules in databases. *ACM SIGMOD Record, 27*(1), 41-46.

Lu, J., Yu, C. S., & Liu, C. (2003). Learning Style, Learning Patterns, and Learning Performance in WebCT-based MIS Course. *Information & Management, 40*(6), 497-507.

Macfadyen, P. L., & Dawson, S. (2010). Mining LMS data to develop an early warning system for educators: A proof of concept. *Computers & Education, 54*(2), 588-599.

Matthews, S. G., Gongora, M. A., Hopgood, A. A., & Ahmadi, S. (2013). Web usage mining with evolutionary extraction of temporal fuzzy association rules. *Knowledge-Based Systems, 54*, 66-72.

Noesgaard, S. S., & Ørngreen, R. (2015). The effectiveness of e-learning: An explorative and integrative review of the definitions, methodologies and factors that promote e-Learning effectiveness. *Electronic Journal of E-Learning, 13*(4), 278-290.

Palacios, A. M., Palacios, J. L., Sánchez, L., & Alcalá-Fdez, J. (2015). Genetic learning of the membership functions for mining fuzzy association rules from low quality data. *Information Sciences, 295*, 358-378.

Peña-Ayala, A. (2014). Educational data mining: A survey and a data mining-based analysis of recent works. *Expert systems with applications, 41*(4), 1432-1462.

Piccoli, G., Ahmad, R., & Ives, B. (2001). Web-based virtual learning environment: A research framework and a preliminary assessment of effectiveness in basic IT skill training. *MIS Quarterly, 25*(4), 401-426.

Shabana, A., & Samuel, S. (2015). An analysis and accuracy prediction of heart disease with association rule and other data mining techniques. *Journal of theoretical & applied information technology, 79*(2), 254-260.

Siguenza-Guzman, L., Saquicela, V., Avila-Ordóñez, E., Vandewalle, J., & Cattrysse, D. (2015). Literature Review of Data Mining Applications in Academic Libraries. *Journal of Academic Librarianship, 41*(4), 499-510.

Sowan, B., Dahal, K., Hossain, M. A., Zhang, L., & Spencer, L. (2013). Fuzzy association rule mining approaches for enhancing prediction performance. *Expert Systems with Applications, 40*(17), 6928-6937.

Troiano, L., & Scibelli, G. (2014). A time-efficient breadth-first level-wise lattice-traversal algorithm to discover rare itemsets. *Data Mining and Knowledge Discovery, 28*(3), 773-807.

Tsai, H. H., & Chang, A. (2007). The Impact of Learning Motivation on Learning Effect-The Moderator of Perceived Leadership. *Chung Hua Journal of Management, 8*(4), 1-17.

Tsang, S., Koh, Y. S., & Dobbie, G. (2013). Finding interesting rare association rules using rare pattern tree. *Lecture Notes in Computer Science, 7790*, 157-173.

Vlahos, G. E., Ferratt, T. W., & Knoepfle, G. (2004). The use of computer-based information systems by German managers to support decision making. *Journal of Information & Management, 41*(6), 763-779.

Wang, K. L. (2011). Sharing experience of implementation of learning outcomes assessment in Ming Chuan University. *Evaluation Bimonthly, 34*, 21-27.

Wang, X., Liu, X., Pedrycz, W., & Zhang, L. (2015). Fuzzy rule based decision trees. *Pattern Recognition, 48*(1), 50-59.
Weng, C. H. (2011). Mining fuzzy specific rare itemsets for education data. *Knowledge-Based Systems*, 24, 697-708.

Zadeh, L. A. (1965). Fuzzy sets. *Information and control*, 8(3), 338-353.

[http://iserjournals.com/journals/eurasia](http://iserjournals.com/journals/eurasia)