A General Framework for Discovering Sequential Patterns based on Fuzzy Concept

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Abstract

With the increase of data, data mining has been introducing to solve the overloading problem and to discover valid, novel, potentially useful patterns in existing data. However, to discover quantitative data, we face a sharp boundary problem that the traditional data mining techniques can not overcome. To pinpoint this problem, a lot of researches have been applied fuzzy sets to discover patterns, especially in sequential patterns [10][14]. As we know, U. Fayyad et al proposed a unifying process-centric framework for Knowledge Discovery in Database (KDD) [11] which can explain the process from top to toe for the traditional data mining problems. Unfortunately, it fails to be workable in part to describe the process for discovering sequential patterns based on fuzzy concept. Therefore, to have more general viewpoint for discovering of that sort patterns, we devote to proposing a general framework modified from the KDD process. An application is proposed to demonstrate that the framework can be a generalization of the realm problem.

KeyWords: framework, data mining, sequential patterns, fuzzy sets

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一般化的架構來挖掘模糊循序樣式

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摘要

隨著資料的大量增加，資料探勘已經被使用在處理資料過剩的問題，並且在既有的資料中，去挖掘有用的、新的和具有潛力的樣式。然而，我們在挖掘量化型的資料時，卻產生傳統不是 0 就是 1 的切割問題，而這問題是傳統資料探勘方法無法解決的。為了這個問題，已經有許多學者，運用模糊集合來解決[10][14]。另一方面，學者 U. Fayyad 等人，在資料探勘的研究中，有提出一個一般化、以程序為主的架構，來概化知識發現的程序[11]，但很遺憾，他們的架構無法適用在模糊循序樣式探勘中，因此，我們修改了他們的架構，提出另一個架構來一般化這樣的探勘程序。最後，我們提出一個應用來證明這個新架構的可用性。

關鍵詞: 架構、資料探勘、循序樣式、模糊集合

1. INTRODUCTION

Data mining extracts implicit, previously unknown and potentially useful information from databases. The discovered information and knowledge are useful for various applications, including market analysis, decision support, fraud detection, and business management. Many approaches have been proposed to extract information, and mining sequential patterns is one of the most important approaches [2][8][9][15][16][24][31].

The problem of mining sequential patterns was first introduced in the mid 1990s, which discovers patterns that occur frequently in a sequence database [2][23]. An example of sequential pattern is like that after buying a computer a customer is likely to return to buy a scanner and a microphone. The discovered sequential patterns can reveal what items are frequently bought together and in what order they appear. Gathering the sequential information, managers can make it instantly to decide to the next step in competitive business.

In the last few years, researches have been extended the typical sequential patterns to provide more valuable information for decision making. Srikant and Agrawal [26] have proposed generalizations of sequential patterns with a user-defined taxonomy (is-a hierarchy), which could provide more details about different levels. Chen, Chiang, and Ko [9] have proposed a generalization of sequential patterns, called time-interval sequential patterns, which reveals not only the order of items but also the time intervals between successive items. Kim, Lim, Na, and Shim [18] introduced an extend sequence database, of which items in each transaction can attach to quantitative data.

Besides the above-mentioned applications, there are some researches to extend sequential patterns by using fuzzy sets. Chen and Huang [10] extended Chen, Chiang, and Ko [9] research to fuzzy time-interval sequential patterns. Hong, Kuo, and Chi [14] proposed sequential patterns with fuzzy quantitative data. The both researches are to fuzzy quantitative data for discovering sequential patterns in sequence databases.

There are some reasons to support the use of fuzzy quantity in place of crisp one. First, the human knowledge can be represented more naturally and appropriately by fuzzy logic. And how to partition and represent the quantity is a sort of human knowledge. Second, it is widely recognized that many real world situations are intrinsically fuzzy. And the partition of quantity is one of them. Third, fuzzy quantity is simple and easy for users. For example, if we use fuzzy sets to handle the quantities, we can first define the linguistic terms that are meaningful and understandable to users. Then, for each such term we can choose appropriate fuzzy function to represent it.

To have more general viewpoint combining data mining and fuzzy fields for discovering sequential patterns, we devote to proposing a general framework modified from the core process of Knowledge Discovery in Database (KDD) [11]. Two motives have combined to make us modify the traditional KDD process, which can not completely describe the problem of disclosing sequential patterns with fuzzy concept.

(1) At the beginning of the KDD process, the pre-processing step, we are regardless of human-being participations in this step. However, the step might be important if users can take part in it to provide expertise especially in fuzzy problem domain. For discovering precise patterns by human opinion, this step is more important than another step of Pattern Evaluation in the KDD process, which also involves in our framework.

(2) The result of the traditional support computation is either 0 or 1 absolutely, i.e. crisp; however, in fuzzy problem domain, it has to include a value between 0 and 1. Consequently, the support definition of finding so-called fuzzy patterns might be redefined. The general framework emphasizes the significance of this step which is overlooked in the KDD process.

The general framework is constructed by seven steps which point out the related tasks could be done interactively and iteratively. The purpose of the framework also is to establish a relationship between data mining and fuzzy sets researchers who are interested in the both fields. They refer to our framework to treat as the first stage if their researches need to collaborate with the two fields' know-how.

The balance of this paper is organized as follows. In Section 2, we review previous researches on the KDD process and fuzzy data mining. Thereafter, Section 3 presents the general framework, which is established by seven steps. We describe them step by step. Section 4 shows an application about mining sequential patterns based on fuzzy concept to prove this framework availably. Conclusions and future works are finally drawn in Section 5.

2. RELATED WORKS

In research [11], Fayyad et al present a unifying process-centric framework for KDD. The whole KDD process is figured in Fig. 1. It is interactive and iterative steps. We introduce these steps briefly. The first two steps are to comprehend an application domain and extract its target data to be employed for discovery. Then, the further step,

pre-processing, is used to remove outliers and noise in data. The transformation step is to find useful features to represent data, which is depending on the goal of our task. Moreover, the dimensionality reduction or transformation techniques are also involved in this step.

At the following step, Data Mining, we focus on the algorithm selection which is the core of the KDD process. What patterns do we want is important to determine the appropriate models using. Patterns can be represented by forms of summarization, classification, regression, clustering, web mining, image retrieval, association [1] /sequential rules mining, functional dependencies and rule extraction.

At the last two steps, users are participated to judge whether the results are interesting and useful. We than interpret the discovered patterns as well as show them by graphical visualization simultaneously. Finally, the challenged patterns become knowledge.

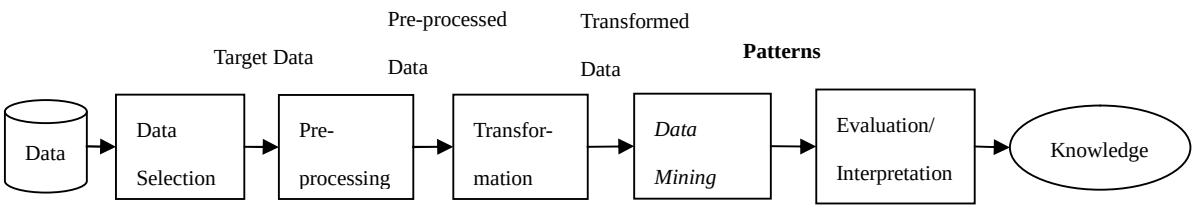

Fig 1. The KDD process [11]

Between Data Mining and Fuzzy Sets, there exists an interdependent relationship for knowledge discovering in databases. The granular computing by fuzzy sets is geared for coping with linguistic domain knowledge and discovering more interpretable outcomes. The fuzzy concept utilizations based on the various functions of data mining are applied in clustering, association rules, function dependencies, data summarization, web applications and image retrieval [22].

In our studies, we find that a number of researches have exploited fuzzy sets to mine fuzzy association rules or sequential patterns from databases. These efforts can be roughly classified into the following: (1) fuzzy representation of item's quantity [19], (2) fuzzy representation of quantitative attribute [13][30], (3) fuzzy product taxonomies or generalization hierarchies [7], (4) fuzzy representation of item importance [28], (5)fuzzy representation of transactions [20], (6) fuzzy support and confidence measure [17], (7) using fuzzy techniques for determining linguistic terms or domain partition [12][27], and (8) using fuzzy techniques to determine rule's interestingness [3][4][5][6].

As the above related studies, we know there are a lot of fruitful researches in

association and sequential patterns mining by fuzzy sets. Between the two patterns discovering, the latter is more interesting than the former because sequences not only reveal item relationship but also provide time constraint. The related researches can be referred to [16].

3. THE FRAMEWORK

In this section, we introduce a general framework to guide research activities for discovering patterns, whose characteristics are sequential and fuzzy. The framework is inspired from the core process of Knowledge Discovery in Database (KDD) [11] and we modify some parts of them to adopt for a generalization of finding sequential patterns with fuzzy concept. The general framework is outlined in Fig. 2 and can be described as falling along the seven steps.

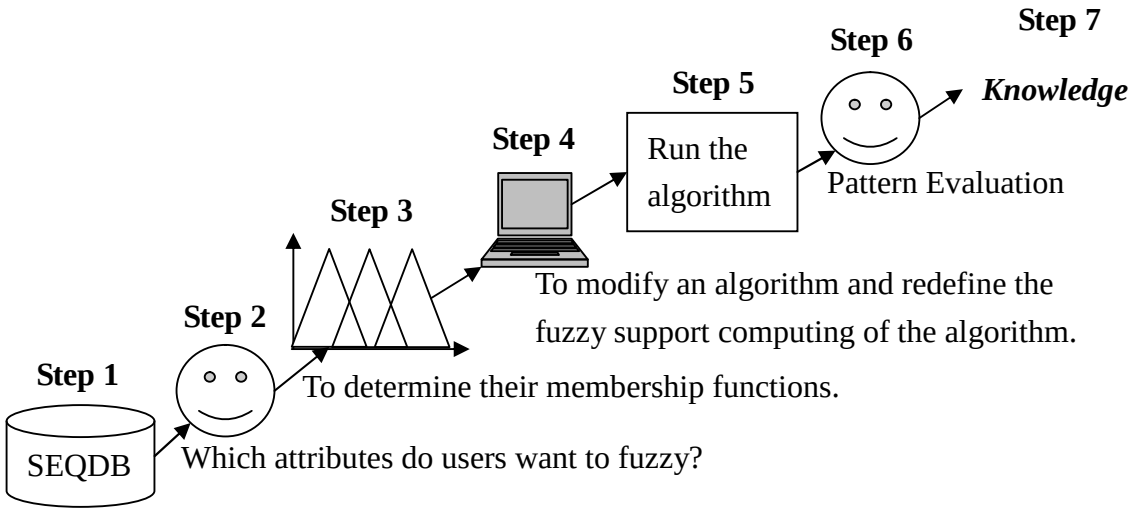

Fig. 2. A general framework for discovering sequential patterns based on fuzzy concept

Step 1. The first step in this framework is to select a target sequence database called SEQDB, whose items in each transaction present quantitative data. Then, data cleaning and pre-processing tasks involve at this step. Data are cleaned and validated to avoid the state of garbage in and garbage out before being put in next step. Thereafter, we handle missing data fields as well as remove outliers and noise in data.

Step 2. The second step, we choice quantitative attributes for which we want to fuzzy in SEQDB. Why do we employ fuzzy sets in quantitative attributes? The answer is: it may face a sharp boundary problem. For instance, what is the meaning of a tall person? As a mathematical expression, we can choice a set of tall persons by that whose height is more than 6ft. The divided approach would classify a person 6.001ft tall as a tall person,

but a person 5.999ft tall is not. This distinction is intuitively unreasonable. Therefore, the example makes us clear that if the data lies on the boundaries of two adjacent quantity intervals, we may either ignore it entirely or overemphasized it. This difficulty can be adequately tackled by using fuzzy sets, for the fuzzy approach allows this quantity to be 50% in one interval and at the same time 50% in another interval. This simple example indicates that the fuzzy approach is better than the traditional partition method because fuzzy sets provide a smooth transition between member and non-member of a set.

Step 3. When we choice attributes for which we want to fuzzy, the running step is to determine the appropriate membership functions to represent their linguistic terms. Two approaches have been used to determine linguistic terms and fuzzy membership functions [21]. The first approach relies on domain experts to specify the functions based on their background knowledge and requirements. The second approach assumes that the functions are obtained by a pre-processing phase that learns the functions from the data, such as learning by neural-network, by genetic algorithm, by clustering method, and by entropy measure [21][25].

Step 4. As we prepare the pre-processing tasks of mining patterns well, the current step is to modify a state of the art algorithm and redefine the support computing according to the research problem. A value by using the classical support computing is one if a tested item or itemset is occurred in SEQDB, otherwise is zero. However, in the fuzzy support calculation, its value might be between zero and one. The given membership functions are dominant to determine the fuzzy support framework.

Step 5. After finishing the above steps, we now commence to execute the algorithm which can generate the complete patterns for our research problem. The experimental configuration could be adjusted during the whole experiment. The performance of the adopted algorithm is the other consideration to discover the patterns effectively.

Step 6. At the step, the domain experts could work together for evaluation patterns out which we find. They can interpret the discovered patterns and remove uninteresting, redundant, conflicting and irrelevant patterns.

Step 7. Finally, the evaluated patterns then become knowledge. We also check for and resolve potential conflicts with previously knowledge by the new discovered knowledge. For the hot knowledge, we can incorporate them in business to make decision strategies.

4. APPLICATION

The seven steps of the general framework have been described by Section 3. Therefore, in this section, we provide a research result to demonstrate that this framework can be a generalization of this realm problem.

The research stems from a problem that the traditional sequential patterns can not reveal the actual time gaps between successive items. Therefore, Chen, Chiang, and Ko [9] have proposed a method to conquer this problem. Although, Chen, Chiang, and Ko have been solved the problem, there still causes a new problem about sharp boundaries. Therefore, Chen and Huang [10] proposed another new pattern called fuzzy time-interval pattern to conquer the sharp boundary problem. The description is depicted as follows.

Problem Description. Discovering sequential patterns can reveal what items are frequently bought together and in what order they appear [2][23]. Although that sort of patterns can provide lots of interesting information, they cannot tell us the time gaps between successive items. Unfortunately, not knowing the time intervals means that, although we know what items will be bought next, we have no idea when the next purchase will happen; this makes it difficult to take the right action at the right time. In view of this problem, Chen, Chiang, and Ko [9] have proposed a generalization of sequential patterns, called time-interval sequential patterns, which reveals not only the order of items but also the time intervals between successive items. The following are some examples of the time-interval sequential pattern: (a) having bought a laser printer, a customer returns to buy a scanner in three months and then a CD burner in six months. (b) A customer revisits website A within a week.

Here, we briefly restate the approach proposed by Chen, Chiang, and Ko [9]. The input of their problem contains a sequence database S, a set $I = \{i_1, i_2, \ldots, i_m\}$ of items and a set $TI= \{I_0, I_1, I_2, \ldots, I_r\}$ of time intervals, where TI is a complete and non-overlap partition of the time domain. A sequence $B=(b_1, \&_1, b_2, \&_2, \ldots, b_{v-1}, \&_{v-1}, b_v)$ is a time-interval sequence if $b_i \in I$ and $\&_i \in TI$ for $1 \le i \le v-1$ and $b_v \in I$. The output is all time-interval sequences which occur frequently in database S. An example of time-interval sequential pattern has a form like (A, I_2, B, I_1, C), meaning that we buy A first, then after an interval of I_2 we buy B, and finally after an interval of I_1 we buy C, where I_2 and I_1 are predetermined time intervals.

Although sequential patterns extended with time-intervals can offer more information than those without time-intervals, the approach may cause the sharp boundary problem. That is, when a time interval is near the boundary of two adjacent

ranges, we either ignore or overemphasize it. For example, let the interval of I_2 be $5 \le t < 10$ and that of I_3 be $10 \le t < 20$, where t is the time gap between two successive items. Then if the time gap between items A and B is near 10, either a little larger or smaller, it is difficult to say the time gap is in I_2 or in I_3. However, according to the original definition of Chen, Chiang, and Ko, it can only be one hundred percent in I_2 or in I_3. This difficulty can be adequately tackled by using fuzzy techniques, for fuzzy set theory allows this time gap to be 50% in I_2 and at the same time 50% in I_3. This simple example indicates that the fuzzy concept is better than the partition method because fuzzy sets provide a smooth transition between member and non-member of a set.

The research problem of Chen, Chiang, and Ko has been described briefly to provide an overview for audiences. The next step which we concern is how the problem can be solved by following our proposed general framework. Then, we have the following statement.

Problem Solved over the Framework. According to the above problem statement, we employ the framework to solve it by steps. The full paper can be referred to [10].

Step 1. The first step is to select a target sequence database which is with quantitative data about time-intervals. The form of this database is shown in Fig. 3. A sequence s is represented as ((a_1, t_1), (a_2, t_2), (a_3, t_3),…, (a_n, t_n)), where a_j is an item and t_j stands for the time at which a_j occurs, $1 \le j \le n$, and $t_{j-1} \le t_j$ for $2 \le j \le n$. Given a sequence s=((a, 1), (b, 4), (e, 29)) where Sid=10, then we know that item a occurs at time 1, b at time 4 and e at time 29.

Sid	**Sequence**
10	((a, 1), (b, 4), (e, 29))
20	((d, 1), (a, 2), (d, 24))
30	((b, 1), (a, 11), (e, 28))
40	((f, 1), (b, 5), (c, 19))
50	((a, 4), (b, 5), (d, 10), (e, 28))
60	((a, 0), (b, 5), (e, 30))
70	((j, 2), (a, 17), (h, 17))
80	((c, 3), (i, 10), (f, 18))
90	((h, 4), (a, 10), (b, 21))

100	((*g*, 0), (*a*, 0), (*b*, 3), (*e*, 30))

Fig. 3. A sequence database with time-intervals.

Step 2. Referred to the database of Fig. 3, the next step is to choice a quantitative attribute to fuzzy. As we discover fuzzy time-interval patterns, a time-interval can be calculated by time tags between two items. Consequently, we compute the time-interval values as $ti_j = |t_{j+1} - t_j|$, where j=1, 2, …, n-1. For example, if we have a sequence s as ((a, 1), (b, 4), (e, 29)), then its time-interval values are 3 and 25.

Step 3. Since we adopt fuzzy techniques to discover fuzzy time-interval patterns, the next step is to provide fuzzy membership functions to determine support values for patterns. Suppose we want to represent a time-interval (denoted as ti) by using three linguistic terms: *Short*, *Middle*, and *Long*. Their membership functions can be represented as follows.

$$\mu_{Short}(ti) = \begin{cases} 1, & ti \le 2 \\ \dfrac{15 - ti}{13}, & 2 < ti < 15 \\ 0, & ti \ge 15 \end{cases} \qquad \mu_{Middle}(ti) = \begin{cases} 0, & \text{either } 2 \le ti \text{ or } ti \ge 28 \\ \dfrac{ti - 2}{13}, & 2 < ti \le 15 \\ \dfrac{28 - ti}{13}, & 15 < ti < 28 \end{cases}$$

$$\mu_{Long}(ti) = \begin{cases} 0, & ti \le 15 \\ \dfrac{ti - 15}{13}, & 15 < ti < 28 \\ 1, & ti \ge 28 \end{cases}$$

Fig. 4. The fuzzy membership functions for time-interval concept.

By applying the fuzzy functions above, we find that the time-interval value 3 is 0.92/*Short* + 0.08/*Middle* + 0.0/*Long* and the time-interval value 25 is 0.0/*Short* + 0.23/*Middle* + 0.77/*Long*.

Step 4. In this step, we start to choice some algorithms to discover patterns. There are two state of the art algorithms, Apriori and PrefixSpan, to modify for fitting the research problem. The first algorithm is based on breadth first search, stage by stage method that any sub-pattern of a frequent pattern is also frequent [2][26]. The second one [15][23][24] employs the depth first search, memory-based idea, that is, dividing the original database into smaller sub-databases which is saved by memory and solving them recursively. The support computation of fuzzy time-interval patterns also needs to redefine. The detail of its support definition can be referred to Chen and Huang's research [10].

Steps 5, 6, and 7. Since the tasks of the following Step 5, 6, and 7 are similar to Data Mining, Evaluation/Interpretation, and Knowledge steps of the KDD process, we do no redundant explanation for them.

5. CONCULSIONS AND FUTURE WORKS

In this paper, we proposed a general framework to guide research activities for discovering sequential patterns based on fuzzy concept. Our main idea in the proposed framework is to provide the methodical steps for scholars who are interested in the related researches of data mining and fuzzy fields.

Compared with the first four steps of the KDD process, steps 1, 2, 3, and 4 of our framework are more special for patterns discovering by fuzzy concept. All of them are focus on how to introduce fuzzy sets into sequential patterns mining problem. The works of the remainder steps are similar to the last three steps of the KDD process.

The framework presented in this paper could be beneficial for data mining and fuzzy sets fields. Not only helps it the two field's researchers communicate each other, but also stimulates more new integrated researches from data mining and fuzzy sets. An application has been demonstrated that the framework is collaborative and workable.

In our future research, we will apply the framework proposed here to additional applications for a variety of sequential patterns discovering based on fuzzy concept. The framework also can extend and examine to discover association rules with fuzzy concept in the future.

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