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ORIGINAL ARTICLE

Discovery of temporal association rules with

hierarchical granular framework

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| KEYWORDS  Data mining;  Association-rule mining;  Temporal association rules; Item lifespan;  Time granules | Abstract | Most of the existing studies in temporal data mining consider only lifespan of items to |
| find general temporal association rules. However, an infrequent item for the entire time may be fre-quent within part of the time. We thus organize time into granules and consider temporal data min-ing for different levels of granules. Besides, an item may not be ready at the beginning of a store. In this paper, we use the first transaction including an item as the start point for the item. Before the start point, the item may not be brought. A three-phase mining framework with consideration of | |

the item lifespan definition is designed. At last, experiments were made to demonstrate the perfor-

mance of the proposed framework.

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1. Introduction

Data mining can help derive useful knowledge from databases.

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Among its technology, association-rule mining [1,3,28] considers frequency relationship among items and is commonly applied to many applications. A transaction usually includes the items bought and the time of its occurrence. Besides, the periods for items to be exhibited are also important. Some researches about temporal data mining were thus presented [27]. For example, the time period for an item may be the entire time interval of a database [5], the duration from the first occurring time of the item to the end of a database [20], or the on-shelf time periods of the item [8]. However, an infrequent item for the entire time interval may be frequent within part of the time.

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| Discovery of temporal association rules | 135 |
| In this paper, we thus organize time into granules and con-sider temporal data mining for different levels of granules. We | granules of features to speed up the mining process of associ-ation rules [10]. |

use the first transaction including an item as the start point for the item. We propose a three-phase mining framework with consideration of the above item lifespan definition to mine temporal association rules with time granules from a temporal database. According to the definition of item lifespan, in the first phase, each elementary time interval is processed. The temporal frequent itemsets within the above intervals are first found, and then the itemsets are identified as candidate tempo-ral frequent ones in all the time granules of the upper level of the hierarchy. These candidates are then judged for being tem-poral or not at each level of granules. Additional database scans may be needed to find the actual supports of the candi-dates. In the third phase, the possible candidate association rules are derived from the temporal frequent itemsets at each level. Their confidence values are then calculated and com-pared with the minimum confidence value to get the final tem-poral association rules.

The organization of the paper is stated below. Related works are given in Section 2. The problem to be solved is described in Section 3. The proposed algorithm with consider-ation of the first transaction appearance period is presented in Section 4. The performance of the proposed approach is shown in Section 5. Conclusions and future works are finally given in Section 6.

2. Review of related works

Temporal data mining is popular in recent years. It analyzes temporal data to get patterns or regularities. There are many techniques included in temporal data mining. Sequential asso-ciation mining [2], cyclic association mining [22], stock trading rule mining [11], patent mining [12], clinical mining [25], image time series mining [15], software adoption and penetration mining [23], temporal utility mining [9,29], fuzzy temporal mining [6,16,17], and calendar association mining [21] all belong to it. There are also a variety of applications for tempo-ral data mining. For example, Patnaik et al. used temporal data mining to efficiently manage the cooling system in data centers [24], and Rashid et al. adopted it for finding the corre-lation among sensor data [26].

Chang et al. considered the temporal mining problem of products exhibited in a store [5]. They proposed the concept of common exhibition to find patterns. In a common exhibi-tion period, all the items in an itemset need to be on the shelf at the same time. Lee et al. then used it to discover general tem-poral association rules for publication databases [20]. Ale and Rossi then considered the transaction periods of products [4], instead of their exhibition periods, for finding temporal associ-ation rules. Besides, different products may have different on-shelf properties. For example, a popular product may be sold out quickly, and then be supplied and on shelf soon. It is thus intermittently on-shelf and off-shelf in the entire time [18].

As to hierarchical temporal mining, Li et al. proposed an approach to discover calendar-based temporal association rules [21]. That approach could mine rules according to differ-ent calendar constraints including years, months and days. Chen et al. proposed a hierarchical strategy for video event detection from video databases [7]. They divided the frequent actions into two types, namely pre-actions and post-actions by pre- and post-temporal windows. Fang and Wu used

In this paper, we consider the phenomenon that an itemset may not be frequent in the entire time interval, but may be fre-quent in a partial time interval. We thus organize the time into different levels of granules and find the temporal association rules at each level. This paper is extended from our previous work [19] with different consideration of effective time inter-vals. Here we use the first occurring transaction of an item as the start point for the item. Before the start point, the item may not be brought since it is not ready. This definition is of the benefit that it is not necessary to require the exact on-shelf time of each item in advance.

3. Problem statement and definitions

To describe the problem of hierarchical temporal association rule mining clearly, assume a temporal database (abbreviated as TDB) in Table 1 is given. Four items are included in the transactions, denoted A to D.

In addition, there is a pre-defined hierarchy with time gran-ules in three levels, in which there are four basic time periods, denoted as p1 to p4, and the time granules are in three levels in the hierarchy, as shown in Fig. 1. Based on Fig. 1 and Table 1, {C} ? {D} is one of hierarchical temporal association rules occurring in the time granule p12. The goal of this paper was to mine such temporal association rules, and the detailed def-initions and examples will be described as follows.

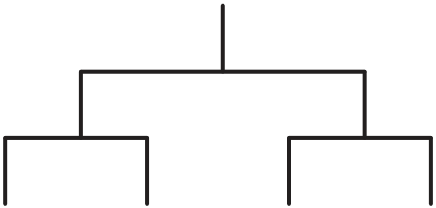
The terms related to the hierarchical temporal mining under the first occurring transaction periods of items are explained below.

Definition 1. P = {p1, p2, . . ., pj, . . ., pn} is a set of mutually disjoint time periods, where pj denotes the j-th time period in the whole set of periods, P.

Definition 2. Let I = {i1, i2, . . ., im} be a set of items appearing in a database. If X # I, then X is called an itemset.

Definition 3. Let X be an itemset and t be a time stamp. A transaction T is a pair (X, t).

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| Table 1 | An example of a temporal database. |  |
| Period | TID | Items |
| p1 | Trans1 | D |
| Trans2 | C, D |
| Trans3 | C |
| p2 | Trans4 | D |
| Trans5 | A, C, D |
| Trans6 | A, B, C, D |
| Trans7 | B, C, D |
| p3 | Trans8 | A, D |
| Trans9 | B |
| Trans10 | A, C |
| Trans11 | A, B, C |
| p4 | Trans12 | B, C |
| Trans13 | B, D |
| Trans14 | B, C, D |
| Trans15 | B |
| Trans16 | B, C, D |



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| 136 |  | *p1234* | | | | T.-P. Hong et al. |
|  | *Level 1* | Table 1 is a simple example showing that, the fifth transac- |
| tion {A, C, D} contains three items, A, C, and D, and the time |
| stamp of the transaction is p2. In Table 1, the first time period |
| *Level 2* | *p12* | | *p34* | | is represented as p1, and P includes four time periods, p1, p2, p3, |
| and p4. In this example, the itemset {AB} containing two items |
| *Level 3* | *p1* | *p2* | *p3* | *p4* | is called a 2-itemset. Since the first transaction including the 1- |
| itemset {B} is the sixth transaction in TDB, and the first time |
| period of the transaction and the last time period of the data- |
| Figure 1 | An example of time granules. | | | | base are p2 and p4, respectively, the maximal time period MTP |
| ({B}) of the item B is p2 to p4. Also, the maximal time period of |

{BCD}, MTP({BCD}), is from p2 to p4 based on the maximal

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| Definition | 4. A | temporal | transaction | database | TDB = |

{Trans1, Trans2, . . ., Transy, . . ., Transz}, where Transy is the y-th transaction in TDB.

Definition 5. The maximal time period of an item i, MTP(i), is from the time period of the first occurring transaction of the item to the last time period of the temporal database.

Definition 6. The maximal time period of an itemset X, MTP (X), represents the common time period of the maximal time periods of all items in X in a temporal database TDB.

Definition 7. A hierarchy of time granules, HTG, is composed of a set of basic time periods. In addition, a time granule pgl.g represents the g-th time granule in the l-th level of the hierar-chy, and it consists of the basic time periods contained by the time granule pgl.g.

Definition 8. The count c(i, p) of item i in a basic time period p is the number of transactions with i in p.

Definition 9. The relative support rsup(i, pg) of item i in a hier-archical time granule pg is the number of transactions with i in its maximal time period of pg over the number of all transac-tions within its maximal time period of pg.

Definition 10. The relative support rsup(X, pg) of itemset X in a hierarchical time granule pg is the number of transactions including the itemset X in its maximal time period of pg over the number of all transactions in its maximal time period of pg.

Definition 11. Let min\_rsup be a given minimum relative sup-port threshold. If rsuppg(X) = min\_rsup, X is called a hierarchi-cal temporal frequent itemset (abbreviated as HTFI).

Definition 12. Assume X is a hierarchical temporal frequent q-itemset with items (x1, x2, . . ., xq), q P 2. The relative confi-dence rconf(R, pg) of a hierarchical temporal association rule

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| within a time granules pg, which is denoted as {x1^. . .^xk-�1^xk+1^. . .^xq} ? {xk}, is shown below:  rconfð x1 ^ . . . ^ xk�1 ^ xkþ1 ^ . . . ^ xq  ¼ rsupðfx1; x2; . . . ; xk�1; xkþ1; . . . ; xqgÞ � rsupðXÞ �; fxkg; pgÞ |

Definition 13. Let min\_rconf be a given minimum relative con-fidence threshold. For a rule R, if rconf(R, pg) = min\_rconf, R is called a hierarchical temporal association rule (abbreviated as HTAR).

time periods of the three items, B, C and D. By considering Fig. 1, the hierarchy is composed of four basic time periods in the temporal database, p1, p2, p3, and p4, and the second time granule pg2.2 in the second level of the hierarchy is com-posed of p3 and p4. Since item B appears in Trans6 and Trans7, within the first basic time period p2, the count value c({B}, p2) of the item in p2 is the value of 2. Accordingly, the rsup({B}, pg2.1) = 2/4 = 50%. In this example, the maximal time period of the item B is set as pg2.1 and only p2 contains the item B. That is, the number of transactions containing B and all the transactions in p2 are 2 and 4, respectively. Also, the rsup ({AB}, pg2.1) = 1/4 = 25% since the maximal time period of the itemset {AB} in pg2.1 only includes p2, and the number of transactions including {AB} and all the transactions in p2 are 1 and 4, respectively. Further, the rsup({CD}, pg2.1) = 50%. If the min\_rsup = 30%, then the itemset {CD} is a hierarchical temporal frequent itemset within the time granule pg2.1. Since the rsup({C}, pg2.1) = 62.5%, the rconf({C} ? {D}, pg2.1) = 50%/62.5% = 80%. It is then compared with min\_rconf.

Based on the above definitions, the problem to be solved is to find the hierarchical temporal association rules with their actual relative support and confidence values within the max-imal time period of the itemset of a time granule being larger than or equal to a predefined minimum relative support threshold min\_rsup and a predefined minimum relative confi-dence threshold min\_rconf, respectively.

4. The proposed algorithm

The proposed approach considers the first occurring transac-tion period information of products and is processed in three phases. It also adopts a predicting strategy which can reduce the number of data scan by the upper-bound support. Basi-cally, the proposed method is a level-wise algorithm which mines the frequent itemsets level by level and period by period. The main contribution of the proposed method is to reduce the number of data scanning, which can be approved by the exper-imental results later. The mining procedures of the proposed algorithm are stated as follows.

The TPPF algorithm (three-phase algorithm with predict-ing strategy considering the first occurring transactions of items) is as follows:

INPUT: A temporal database TDB with n transactions, each of which consists of transaction identification, transac-tion occurring time and items purchased, m items in TDB, a hierarchy with time granules HTG, the minimum relative support threshold min\_rsup, and the minimum relative con-fidence threshold min\_rconf.

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| Discovery of temporal association rules | 137 |

OUTPUT: A final set of all hierarchical temporal associa-tion rules, HTAR.

Phase 1: Find temporal frequent itemsets.

STEP 1: Initialize the PTT (Periodical Total Transaction) table as a zero table, in which the row number is the time period number of the bottom level in the hierarchy of time granules, and each entry in the table is set as 0.

STEP 2: Find the periodical total transaction number pttj within each time period pj of the bottom level in HTG as the number of transactions in pj, and put it in the PTT table.

STEP 3: Initialize the first appearance period FAP table as an empty table, in which each tuple consists of two fields: an item and the time period p of the first transaction including it in TDB.

STEP 4: Find the time period p of the first transaction including the item I in TDB, and then put the item and its first time period p in FAP.

STEP 5: Find the temporal frequent itemsets within each time period p by the Finding-Individual-TFI proce-dure. Let the set of returned temporal frequent itemsets for the j-th time period pj of the bottom level of HTG be denoted as TFIj.

Phase 2: Find all hierarchical temporal frequent itemsets.

STEP 6: Initially set the set of hierarchical temporal fre- quent itemsets (HTFI) as empty.

STEP 7: For each time period granule pg in each of all the other levels in HTG other than the bottom one, do the following substeps.

(a) Get the union of all TFIj’s in pg, and denote them as possible itemsets, PIpg.

(b) For each itemset X in the set of PIpg, find the maximum common period MCPX of all the items in X within the time granule pg by using the FAP table and then calculate the relative support upper-bound rsubpg,X of X within the time granule pg as:

rsubpg;X ¼ 0 @ pj2MCPx^pj # pg X cactual j;X þ pj2MCPx^pj # pg X cub j;X 1 A , pj2MCPx^pj # pg X pttj;

where cactual j;X is the actual count of X within the j-

th time period pj of the time granule pg by the sets of all TFIj of the time granule pg, and cub j;X is the upper-bound (¼ k � pttj � 1) of X within pj of pg by the PTT table.

(c) For each itemset X in set of PIpg, calculate the relative support lower-bound rslbpg,X of X within the time granule pg as:

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| rslbpg;X ¼ | pj2MCPx^pj # pg X cactual j;X | , pj2MCPx^pj # pg X pttj: |

(d) Store each X in the set of PIpg whose rslbpg,X exceeds the minimum relative support thresh-old min\_rsup into the set of hierarchical temporal frequent itemsets (HTFI) and set

(e) For each itemset X remaining in the current set PIpg = PIpg � X.

of PIpg, scan the transactions to calculate the relative support value rsuppg,X within the time granule pg as:

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| rsuppg;X ¼ | pj2MCPx^pj # pg X Cj;X | , pj # pg X pttj; |

(f) Store each X in the set of PIpg whose relative support exceeds the minimum relative support threshold min\_rsup into the set of hierarchical temporal frequent itemsets (HTFI); otherwise, set PIpg = PIpg � X.

Phase 3: Find all hierarchical temporal association rules.

STEP 8: Initially set the set of hierarchical temporal fre- quent sub-itemsets (HTFS) as empty.

STEP 9: For each itemset X in the HTFI set, do the follow- ing substeps:   
 (a) Generate all possible sub-itemsets of the item- set X.

(b) For each sub-itemset s, check whether the sub-itemset s with the same common period exists in the HTFI set. If it does, put the sub-itemset s in the HTFS set and use the relative support value of s in the HTFI set as the relative sup-port value of s in the HTFS set; otherwise, scan the transactions of the required time peri-ods to find the relative support value of s, and then put s with its relative support value in the HTFS set.

STEP 10: For each itemset X with items (x1, x2, . . ., xr) in the HTFI set, generate all possible hierarchical temporal association rules and calculate the rela-tive confidence value rconfpg,R of each possible rule R.

STEP 11: Output the final set of hierarchical temporal asso-ciation rules (HTAR) exceeding the minimum rel-ative confidence min\_rconf.

After STEP 11, all the rules in the set of HTAR have been found from the temporal database. The Finding-Individual-TFI procedure used in STEP 5 is described below. Here, the tradi-tional Apriori algorithm is adopted to derive frequent itemsets from the transactions within a time period.

The Finding-Individual-TFI procedure is as follows:

Input: A set of transactions TDBj within a time period pj. Output: The temporal frequent itemsets TFIj in pj.

PSTEP 1: Set r = 1 and Cjr to include all the items in the time period pj.

PSTEP 2: For each temporal candidate r-itemset in the set of Cjr within TDBj, scan TDBj to store the

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| 138 | T.-P. Hong et al. | |
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| itemset whose count exceeds the threshold of k � pttj into TFIjr.  PSTEP 3: Generate the temporal candidate set Cj(r+1) from TFIjr in the current time period pj. The r-sub-itemsets of each candidate in Cj(r+1) must exist in TFIjr.  PSTEP 4: If Cj(r+1) is not null, set r = r + 1 and repeat k¼1TFIjk PSTEPs 2 to 3; otherwise, set TFIj ¼Sk¼r  5. Experimental results  In this section, the experimental results for showing the prun-  ing effects and efficiency of the proposed TPPF approach are |
| Figure 2 | The pruning effects of the two approaches on the |
| synthetic data. | |

presented. As a comparison, the basic three-phase algorithm   
without consideration of the predicting strategy (named TP-

HTAR, Three-Phase algorithm for Hierarchical Temporal Association Rules) is derived from the proposed TPPF approach. The experimental environment included a personal computer with 3.0 GHz CPU and 2 GB memory, running J2SDK 1.6.0. The two methods were performed on the same machine using the same program language, data and parame-ter settings. The execution time included data input, generation of frequent itemsets and result output.

5.1. Experimental datasets

From the results in Fig. 2, it can be observed that TPPF needed less database scans than TP-HTAR. It was because TP-HTAR purely used the level-wise technique to handle the problem of hierarchical temporal issues. In addition, if all the frequent itemsets in each basic period were identified as possible hierarchical temporal itemsets, then the transactions in the time periods, in which the relative supports of the pos-sible itemsets were unknown, had to be scanned to find the actual relative supports for itemsets. Thus, the TP-HTAR per-formed worse than the proposed TPPF in terms of avoiding

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| Two datasets including synthetic data and real data were used to conduct the comprehensive empirical study. In terms of the synthetic data, it was generated by the public IBM data gener-ator [14]. The temporal database was generated by the model used in [18]. The detailed information of the synthetic data is shown in Table 2.  To attack the insufficiency of the synthetic data, we also adopted a real dataset Foodmart as the other experimental data. The Foodmart database is a well-known dataset from Microsoft SQL Server 2000. It includes 21,556 transactions and 1600 items.  5.2. Experimental results on synthetic data | unnecessary data scans.  The experiments were then conducted to evaluate the effi-ciency of the two algorithms, TPPF and TP-HTAR, for the hierarchical temporal mining issue, and Fig. 3 shows the | | | | | | | |
| results | of | the | two | algorithms | working | on | the |
| T10I4N4KD100KP16 dataset with 16 basic periods and 4 levels for the synthetic datasets with the thresholds varying from 0.3% to 0.4%.  The results clearly show that the execution time of the TPPF for the hierarchical temporal mining issue performed better than the other algorithm, TP-HTAR. The reason was the same as that mentioned above. Since TPPF obviously needed less data scans than TP-HTAR, the time cost of unnec-essary data scans could effectively be saved by the TPPF. | | | | | | | |

The synthetic T10I4N4KD100KP16 dataset was first used in   
the experiments. It was divided into 16 basic time periods,   
which were organized into a hierarchy of 4 levels. Fig. 2 shows

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| the pruning effects of the two approaches, TP-HTAR and TPPF, for the T10I4N4KD100KP16 dataset for different thresholds within 0.3–0.4%. | | |  | |
| Table 2 | Parameter values of the synthetic data. | |
| Parameter | Description | Default |
| value | | |
| T | The average length of items per | 10 |
| transaction | | |
| I | The average length of maximal potentially | 4 |
| frequent itemsets | | |
| N | The total number of items | 4000 |
| D | The total number of transactions | 100,000 |
| Figure 3 | The execution time of the two approaches on the |
| P | The number of basic periods | 16 |

synthetic data.

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| Discovery of temporal association rules | | 139 | |
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| Figure 4 | Execution time of generating association rules under | Figure 5 | The execution time of the two approaches on the real |
| different minimum confidences on the synthetic data. | | dataset Foodmart. | |

Accordingly, TPPF could be more efficient than TP-HTAR for the synthetic dataset.

5.3. Experimental results on real data

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| In addition to the above experimental results of discovering the frequent itemsets, we also conducted an empirical study for the efficiency of generating association rules based on the dis-covered frequent itemsets. Fig. 4 shows the experimental results of evaluating the rule generation using the frequent itemsets yielded by different minimum relative support set {0.3%, 0.32%, 0.34%, 0.36%, 0.38%, 0.4%}. That is, six sets were employed to generate associations. The minimum confi-dence values ranged from 0.2 to 0.8.  From Fig. 4, the experimental discovery can be summarized as follows. First, all of the execution time is quite close, which is within one second. It means the rule generation time is very small when compared with that of generating frequent item-sets. The reason is that, the rule generation is simpler and takes much less time than generating frequent itemsets. Second, whatever the minimum confidence is, the larger the minimum relative support, the smaller the execution time. The reason is when the minimum relative support becomes larger, less fre-quent itemsets will be generated and thus the rule generation cost will be less as well. Third, for each set, the differences of execution time for generating rules under different minimum confidence values are very slight. The reason is that the confi-dence checking time depends on the number of frequent item-sets generated, but not on the confidence thresholds. Besides, larger minimum confidence values will get more rules and thus | In addition to synthetic data, a real dataset Foodmart was tested in the experiments. The transactions were divided into 10 time periods and the time hierarchy was organized in three levels, with 1, 5 and 10 time periods, respectively. Fig. 5 shows the differences in the execution time needed by the two algo-rithms for different thresholds, varying from 0.6% to 0.7%. The experimental results show that the algorithm TPPF per-formed much better than TP-HTAR since the number of data scans of TPPF was much fewer than those of TP-HTAR. The results are an echo of Figs. 2 and 3.  For showing the performance of generating association rules, similar to Fig. 4, six sets with different minimum relative support values yielded by the proposed methods were adopted in the experiments, which are {0.6%, 0.62%, 0.64%, 0.66%, 0.68%, 0.7%}. Fig. 6 shows the experimental comparisons for rule generation, which delivers some discovery. First, the execution time for each set is very close to each other even using different minimum confidence values. The reason is the same as above. That is, the confidence checking time depends on the numbers of frequent itemsets generated, but not on the confidence thresholds. Second, the performance for smaller confidence value is worse than that for larger confidence val-ues. The reason is that the former will get more rules and thus need more time to generate them out. |

need more time to generate them out. But rule generation is

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| very quick and thus there is no significant difference for differ-ent thresholds.  In general, the values of the two parameters min\_rsup and min\_rconf affect the performance of the proposed approach. When min\_rsup is set lower, more candidate itemsets are gen-erated and thus the needed computational time becomes more as well. Similarly, when min\_rconf is set lower, more rules are generated which needs more computational time. These char-acteristics can be easily observed from Fig. 4 as well. Besides, the minimum support and confidence values are usually deter-mined according to the data characteristics and user require-ment. There are some studies focusing on this issue, but it is beyond our discussion here. Some scholars [13,30,31] adopt the to p–k mining approach to find the results, instead of set-ting the two thresholds. |  | |
| Figure 6 | The execution time of generating association rules |
| under different minimum confidences on the real data. | |

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| 140 | T.-P. Hong et al. |
| 6. Conclusions | [8] [Y.L. Chen, K. Tang, R.J. Shen, Y.H. Hu, Market basket](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0040) analysis in a multiple store environment, Decision Support Syst. |

In this paper, we introduce a new concept of temporal associ-ation rule mining with a hierarchy of time granules to find hier-archical temporal association rules in temporal databases, and

[40 (2) (2005) 339–354](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0040).

[9] [C.J. Chu, Vincent S. Tseng, T. Liang, Mining temporal rare](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0045)

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| [utility](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0045) | [itemsets](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0045) | [in](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0045) | [large](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0045) | [databases](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0045) | [using](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0045) | [relative](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0045) | [utility](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0045) |

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we also present the effective approach (abbreviated as TPPF) [(2008) 2775–2792](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0045).

to find such rules. In particular, an effective strategy is designed to predict the upper-bound of support values for itemsets. The strategy can be used to remove unpromising itemsets at an early stage in the process, and the proposed TPPF can effectively reduce the computational cost of scan-ning a temporal database. Experiments were also made, with results showing the proposed TPPF outperformed the other one TP-HTAR in reducing database scan and computational time.

The future research directions of this work are as follows.

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| [granules](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0050) | [for](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0050) | [mining](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0050) | [association](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0050) | [rules,](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0050) | [Int.](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0050) | [J.](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0050) | [Artificial](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0050) |

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First, we will attempt to investigate the incremental problem 1823.

of hierarchical temporal association rule mining. That is, based on this work, we will design a method to mine the new result without performing the whole mining procedure at database modification. Second, the optimal minimum support and con-fidence will be approximated by machine learning techniques. Third, actually, this work is the beginning of hierarchical tem-poral association rule mining. In the future, more efficient min-ing algorithms such as FP-growth will be adopted as the

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solutions to accelerate the mining process and more mining [(1) (2012) 23–44](http://refhub.elsevier.com/S2210-8327(16)00004-1/h0075).

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