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Analysis of User Movement Behaviour Pattern Mining Approaches for Mobile Environments

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Abstract: The advances in wireless communications and mobile device technologies not only accentuate various wireless communications applications but also enable the provision of plentiful kinds of mobile services for users. Mobile service systems offer users useful information ubiquitously via mobile devices. Based on changeable user movement behaviour patterns (UMBPs), mobile service systems have the capability of effectively mining a special request from abundant data. In this paper, UMBPs are studied in terms of the problem of mining matching mobile access patterns based on joining the following four kinds of characteristics, U,L,T, and S, where U is the mobile user, L is the movement location, T is the dwell time in the timestamp, and S is the service request.

Keywords: Data mining, mobile access patterns, mobile services

I. INTRODUCTION

In mobile service environments, mobile users may request various kinds of services and applications through mobile devices laptop computers from arbitrary locations at any time via3G, WiMax, wireless LAN, or other wireless networking technologies. User movement behaviour patterns (UMBPs), which may consist of mobile users, movement locations, dwell time in timestamps, and service requests, are an important factor for mobile service systems. To achieve a quick response from the system, data mining, which has been used successfully in many applications, is one of the most promising technologies used to full fil a dynamic service request.

In accelerating the data access time [1], researchers have studied the problem so facing and perfecting [2] to improve system performance in Web service environments. By extracting structure-based patterns, related services can be efficiently recommended to users to help them receive desired information in a short time. Related items can also be pre fetched to reduce the search cost for increasing the access efficiency of Web service servers. From a Web service management point of view[2], the Web service organization can be rearranged or restructured tofit the users' interests by taking advantage of recommendations and predictions. Traditional mobile service systems are inadequate in handling complex UMBPs without taking U (mobile users),L(movement locations),T (dwell time in timestamps), and S(service requests)

Into serious consideration. Over the past few years, some studies have employed data mining techniques to discover interesting patterns from Web logs [3], [4] or large databases [5]. Although some recent studies have made progress on data mining in mobile service systems, they were mostly focused on issues such as moving path mining or service request log mining [6]. Researchers have also studied the problems of location tracking and resource allocation [7-10]. Moreover, by modelling UMBPs via maximum weight bipartite graph matching [11], this prediction mechanism provides appropriate recommendations for users in terms of the spatial movement locations of each mobile user with requested services in different time intervals. Nevertheless, for acquiring an appropriate recommendation and a precise prediction, the four relational patterns of U,L,T and S must be considered simultaneously.

Recently, similar approaches to analysing the pattern so fuser behaviours have received much attention. In this paper, a data mining approach is studied and analysed for efficiently discovering UMBPs in a mobile service environment, namely matching mobile access patterns (MMAPs), which include the user's movement locations associated with requested services in different time intervals. In addition, the proposed approach is implemented in a data mining system integrated into a novel context-aware mobile guiding platform .The more applications make use of relational database management systems (RDBMSs) as their primary storage mechanism, the more doubt arise concerning the query capabilities of RDBMSs to support these applications. Accordingly, in this paper, alternative exact and approximate strategies are explored using an RDBMS to compute the maximum cardinality matching of relations U, L,T, and S with the match join weight w. A two-step, match join algorithm and an associated tree-based structure are also studied.

II. MATCHING MOBILE ACCESS PATTERNS

The match joins using maxflows (MJMF) requires knowledge of the attributes that served as inputs to the match join weight w. Second, match joins using sort combinations (MJSC) requires knowledge of the match join weight w that is more detailed. A family of match join weights is characterized and then yields a maximum match by MJSC. Mining matching UMBPs can be comprehended by operating on relational flows to generate the max flow of match joins by means of MJMF. The transformation from a matching problem to the max flow proble m can be divided into three phases :grouping nodes, building the reduced graph, and exercising he max flow algorithm.

MJSC computes the match join of the four input relations byfirst dividing the relations into groups of candidate matching tuples of U, L, T and S and, second, by operating the match join within each group. The steps of the algorithm are as follows:

Step 1: Perform an external sort of four input relations on allattributes involved withw.

Step 2: Iterate through the relations and generate the next groupG of the tuples ofU,L,T, andS.

Step 3: Within G, combine the four subsets of U, L, T, andS tuples. Compared to the operation of combine-join, theiterators operating in the table can be advanced as soon asmatches are found.

III. MININGUSINGASSOCIATEDTREES

A novel method is presented to calculate the relationships of the associated tree-based patternsin the candidate cardinality matching tuples. The numerical values of these relationships represent the degrees of U, L, T and S matching relations of a particular associated tree-based pattern in these candidate cardinality matching tuples. Finally ,a comprehensive experimental evaluation of the proposed methods is presented using synthetically generated data that simulate real-world user movement behaviours. The approach of mining frequent associated tree patterns can be illustrated in the following five steps:

Step 1: The maxflow database DM is scanned to generate a set of frequent 1-tree candidate patterns. If the candidate pattern cannot meet themin_supvalue, it will be pruned.

Step 2: The match join operation is employed to generate frnt 2-tree candidate patterns.

Step 3: The support of each candidate is counted and thein frequent patterns are pruned.

Step 4: The 3-tree candidate patterns are generated to enumerate all the relational patterns, which include the parent child and siblings, by the match join operation.

Step 5: Candidate patterns of(k+1)-trees are repeatedly generated until a set of frequent (k+1)-trees is empty or no candidate is generated.

Algorithm 1 [12] shows the details of mining frequent associated tree patterns. In this algorithm, NC_{Max} is denoted as the maximum count of nodes in frequent associated tree patterns .By candidate generation, the match join operation is performed to produceC_k and L_k,where C_k is a set of k-subtree candidate patterns ,the subscrip tk is the size of eachk-subtree match join candidate and $1\leq k\leq NC_{Max}$ and L_k, which is defined asL_k is a set of associated tree patterns with the set of n match join candidate patterns captured from k variable elements of the tuples, where$1\leq n\leq 4$.

Algorithm 1: Mining frequent associated tree patterns

a. 1:Let C_1^4 be denoted as generating sets of frequent 1-treecandidate patterns
b. 2:Let C_2^4 be denoted as generating sets of frequent 2-treecandidate patterns
c. 3:Let C_3^4be denoted as generating sets of frequent 3-treecandidate patterns
d. 4:LetNC_{Max}be denoted as the maximum count of nodes
e. 5:LetNC_{Min}be denoted as the minimum count of nodes
f. 6: for(i =0;i<4; i++) //C_1^4
g. 7: {
h. 8: C_1^4(C_1^4Param[i]);
i. 9: }
j. 10: SumNode =0; // C_2^4
k. 11: for(i =0;i<6; i++)
l. 12: {
m. 13: Node = C_2^4(C_2^4ParamStr[i], C_2^4Param[i]);
n. 14: if(i == 0)
o. 15: {
p. 16: NC_{Max}= Node;
q. 17: NC_{Min}= Node;
r. 18:}
s. 19: else
t. 20: {
u. 21: if(Node >NC_{Max})
v. 22: NC_{Max}= Node;
w. 23: else if(Node <NC_{Min})
x. 24: NC_{Min}= Node;
y. 25: }
z. 26: SumNode= SumNode+Node;
aa. 27: }
bb. 28: AvgNode = SumNode/6;
cc. 29: SumNode=0; //C_3^4
dd. 30: for(i =0;i<4; i++)
ee. 31: {
ff. 32: Node = C_3^4(C_3^4ParamStr[i], C_3^4Param[i]);
gg. 33: if(i == 0)
hh. 34: {
ii. 35: NC_{Max}= Node;
jj. 36: NC_{Min}= Node;
kk. 37: }
ll. 38: else
mm. 39: {
nn. 40: if(Node >NC_{Max})
oo. 41: NC_{Max}= Node;
pp. 42: else if(Node <NC_{Min})
qq. 43: NC_{Min}= Node;
rr. 44: }
ss. 45: SumNode= SumNode+Node;
tt. 46:}
uu. 47: AvgNode = SumNode/4;

IV. ANALYSIS

The procedure of MJMF is to compress the input relations by using a group-by operation and then build the max flow graph by means of a max flow algorithm. It will be shown that MJMF always generates maximum matching and is efficient if the compression is effective. In addition to MJMF, an associated tree-based technique is used to determine the relationships among data in the structure. An associated tree-based pattern, extracted from candidate cardinality matching tuples, is obtained based on the given minimum support (min_sup) value.

V. COMPARATIVE STUDY

Mobile user acquires the services from the mobile environment and is capable of being identified and tracked. If mobile users use the acquired service longer than the optimum time, the service is regarded as interesting or useful information service. The match join using max flows is used to generate maximum matching of services for analysing mobile users behaviour in efficient manner. Frequent movements patterns of mobile users can be mined using associated trees . Mining gives accurate result of behaviour patterns of user movement.

VI. CONCLUSION

In this paper, a data mining method for mining UMBPs is studied. The UMBPs can be regarded as the numerical value of the weight w of the match joins of U,L,TandS. In general, the set of UMBPs is a subset of thew-joins ofU, L,T and S, such that each tuple of U,L, T and S in thew-joins contributes at least one matched tuple to the set of UMBPs .Match joins and their generalizations belong to a wide category of matching problems that have brought about a great deal of attention in disciplines, including operation research and theoretical computer science. It is showed that the simple approach of computing the full w-joins and then applying standard graph-matching algorithms and the DBMS primitives ofgrouping, sorting, and joining could beutilized to yieldefficientmatch join operations. Moreover, a novel mining scheme was proposed to mine associated trees. Furthermore, an efficient algorithm was introduced to count the support values and the weighted support values from the matching candidate patterns of frequent occurring k-trees in the max flow database.

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