MINING AND VISUALIZATION OF ASSOCIATION RULES OVER RELATIONAL DBMSs

By

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To my family

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As more and more data are collected and stored in multiple databases, data mining over different relational DBMSs is becoming increasingly important. Usually the data sets are stored in some different DBMSs, such as DB2, Oracle, Sybase, etc. Data mining software should be able to use the data from all of these DBMSs. In this thesis we use JDBC (Java Database Connectivity) to achieve this goal. The test DBMSs we used are Oracle and DB2.

We implement the association rule algorithm in the form of SQL queries. Three algorithms in SQL-92 (K-Way Join, 2-Groupby, and Subquery) and three algorithms in SQL-OR (Vertical, GatherJoin and GatherJoin Variant) are implemented and compared to each other based on their performance on different kinds of synthetic generated data sets. Scale-Up experiments have also been conducted for these six approaches.

We develop an association rule visualization system, which includes tabular form and three-dimensional graphics. By providing the user sorting and filtering abilities, this rule visualization system makes it flexible and efficient for the user to manage and understand the association rules. As a result, this visualization system becomes an essential part of our association rule software.

Finally, we compare our association rule software with one of the commercial data mining tools (Intelligent Miner from IBM) in various aspects, such as data accessibility, user interface, input/output, and rule visualization.

CHAPTER 1
INTRODUCTION

As computers are used in more and more areas, large volumes of data have been collected and stored in the database continuously. This kind of data includes the transaction records in supermarkets, banks, stock markets, and telephone companies. With the increasing volume of the stored data, an important issue is to figure out how to find the useful information from these massive history data. Data mining, also known as knowledge discovery in databases, is such a research area to extract implicit, understandable, previously unknown and potentially useful information from data. In Section 1.1 we briefly describe different categories of data mining, such as association rule, clustering, classification, sequential pattern, text mining and active data mining. The limitations of currently available commercial data mining software (especially for association rule) are discussed in Section 1.2 and in Section 1.3, we outline the thesis organization.

1.1 Categories of Data Mining

1.1.1 Association Rule

The typical example of association rule is the Basket data analysis [AGR1994]. In a given database D, all the records consist of two attributes: transaction ID (TID), and the item the customer bought in the transaction. Usually the item attribute in each record contains only one item, so in the database, there will be more than one row for a

transaction ID since each transaction will involve more than one item. Table 1.1 shows one example of the basket data set with four transactions.

Table 1.1 Example Basket Data Set

TID	ITEM
100	1
100	3
100	4
200	2
200	3
200	4
300	1
300	2
300	3
300	5
400	2
400	5

The formal definition of association rule is the following [AGR1993]: Let $\Gamma = \{i_1, i_2, \ldots, i_m\}$ be a set of literals, called items. Let D be a set of transactions, where each transaction T is a set of items such that $T \subseteq \Gamma$. Associated with each transaction is a unique identifier, called its TID. We say that a transaction T contains X, a set of some items in Γ, if $X \subseteq T$. An association rule is an implication of the form $X \Rightarrow Y$, where $X \subset \Gamma$, $Y \subset \Gamma$, and X intersection $Y = \phi$. The support and confidence of an association rule ($X \Rightarrow Y$) are calculated by the following two equations:

$$Support = \frac{The.Number\ Of\ Transaction That\ Contains\ X\ and\ Y}{The Total\ Number Of\ Transactions}$$

$$Confidence = \frac{The\ Number Of\ Transaction That Contains Y}{The\ Number Of\ Transaction That Contains\ X}$$

The rule $X \Rightarrow Y$ holds in the transaction set D if its support and confidence are equal to or greater than the user specified values. The goal of association rules is to find the relationship between any combination of items.

1.1.2 Clustering

The goal of clustering is to identify homogeneous groups of objects based on the values of their attributes [AGR1998]. For a given set of objects (each object has several attributes), the task of clustering is to group some objects together (we call these objects are in one cluster) so that the objects in the same cluster are more similar to each other than to objects in a different cluster. The technique of solving clustering problems falls into two categories: partitional and hierarchical [AGR1998]. For the partitional clustering, the K-means method is widely used. This method first determines K cluster representatives, then assign each object to the cluster with its representative closest to the object such that the sum of the distances squared between the objects and their representatives is minimized. For the hierarchical clustering, it usually starts by placing each object in its own cluster and then merges these atomic clusters into larger and larger clusters until all objects are in a single cluster.

1.1.3 Classification

The classification problem can be described as the following [MEH1996]: For a given database D, each record consists of several attributes. Among all the attributes, one attribute works as *class label*. Such a database is called as *training set*. Table 1.2 shows an example of training set with 3 attributes: age, car type, and risk. Attribute risk (its value is either high or low) is the class label. The goal of classification is to analyze the training set and to develop an accurate description or model for each class using the attributes presented in the data. Many classification models such as neural networks,

genetic models, and decision trees etc, have been developed to solve this kind of problem. Figure 1.1 shows the decision tree of the training set provided by Table 1.2. This decision tree shows that all the persons who are less than 25 years old have a high risk, while in the group of person who are older than 25 years old, the persons who drive sports cars have high risk, and those who drive other vehicles have low risk. The ability to solve classification problems quickly and efficiently is very important to several businesses, such as car insurance companies. In recent years, several algorithms, such as SLIQ [MEH1996] and SPRINT [SHA1996], have been developed to solve classification problems efficiently on large data sets.

Table 1.2 Example Training Set

Age	Car Type	Risk
23	Family	High
17	Sports	High
43	Sports	High
68	Family	Low
32	Truck	Low
20	Family	High

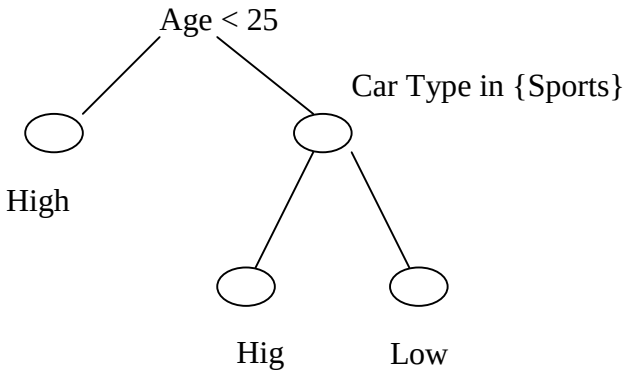


Figure 1.1 Decision Tree

1.1.4 Sequential Patterns

The formal definition of sequential patterns is given in Agrawal and Srikant [AGR1995c]. For a given database D, which consists of customer transactions. Each transaction consists of the following fields: customer-ID, transaction-time, and the items purchased in the transaction. An item-set is a non-empty set of items, and a sequence is an order list of item-sets. We say a sequence A $<a_1, a_2, a_3, \ldots, a_n>$ is contained in another sequence B $<b_1, b_2, b_3, \ldots, b_n>$ if there exist integers $i_1<i_2<i_3<\ldots<i_n$, such that $a_1 \subseteq b_{i1}$, $a_2 \subseteq b_{i2}$, …, $a_n \subseteq b_{in}$. For example, the sequence < (3) (4,5) (8)> is contained in <(7) (3,8) (9) (4,5,6) (8)>, because (3) $\subseteq$ (3,8), (4,5) $\subseteq$(4,5,6), and (8) $\subseteq$(8). A customer sequence is a sequence of item-sets for each customer-ID. The support of a sequence s is defined by the following equation:

$$Support = \frac{The\ Number\ of\ Sequence That\ Contains\ This\ Sequence}{Total\ Number\ of\ Sequences}$$

For the example data set in Table 1.3, We can find all the sequences that have support > 25%, which are < (30) (90) >, and < (30) (40,70) >.

Table 1.3 Sequences of an Example Database

Customer	Customer Sequence
1	< (30) (90) >
2	< (10, 20) (30) (40, 60, 70) >
3	< (30,50,70) >
4	< (30) (40,70) (90) >
5	< (90) >

The goal of sequential patterns is to find the sequences that have greater than or equal to a certain user pre-specified support. Usually the process of finding sequential

patterns consists of the following phases: sorting phase, finding the large item-set phase, transformation phase, sequence phase, and maximal phase.

1.1.5 Text Mining

In the real world, it is very common to find the hidden relationship in the larger text database. For example, it is very useful to find whether the company is shifting its interest from one domain to another. Text mining is very good at handling this situation since the database in full of text, instead of the numeric data. The goal of text mining is to discover the trends in the text database. Lent et al. [LEN1997] developed a system to discover the trends in text database. Their basic idea is to use the existing data mining algorithms and shape query language (SDL) [AGR1995b]. For a given database D of documents (each document consists of text fields and a timestamp, the unit of text is a *word* and a *phrase* is a list of words), they begin with cleansing and parsing the data, and then separating the documents based on their timestamp. Each *word* will be assigned a transaction ID based on its document timestamp. Then the sequential pattern algorithm will be applied for the transformed data to produce the results. The results will be queried using shape query to find the increasing or decreasing trend of the occurrence frequency. The purpose of using shape query language is that a “blurry” match (cares about the overall shape, but not the specific details) is possible. The following is an example of shape query language:

(in 5 (and (no less 2 (any up Up)) (no more 1 (any down Down))))

This statement shows that we are interested in the subsequences five intervals long that have at least two ups (either up or Up) and at most one down (either down or Down).

1.1.6 Active Data Mining

Active data mining combines the technology of data mining and active database. The basic idea [AGR1995a] is to divide the whole data into several sub-data sets. The data mining algorithms will be applied to each sub-data set and the results for each sub-data set will be produced. Because usually the data sets come from data warehousing and thus the volume of data is very huge, dividing the data set to several sub-data sets will not lose the significance of the results. All the rules generated in each sub-data set will be stored in the rule database with some parameters, such as the support and confidence for association rule problems. When the new data comes in, and the volume of new data reached a certain level, the data mining algorithm will be applied to the new data set again and then check the rule database. If one certain rule does not exist, it just stores the rule into the rule database. If this rule exists in the rule database, it will update the parameters of the existing rules in the rule database. The database uses trigger to monitor the parameters in the rule database. Once the condition is met, the specific trigger will be fired. ECA (Event Condition Action) model [CHA1995] can be used for more complex triggers. Figure 1.2 shows how active data mining works.

One example of active data mining is that the supermarket can use association rule algorithm and active data mining to monitor the sale trends. Once the support or confidence parameter for a specific rule reaches the pre-set value, the trigger will be fired and the manager of the supermarket will be notified.

1.2 Problem Statement

Although lots of efforts have been put in the association rule area, and some commercial products, such as MineSet [SGI2000], and Intelligent Miner [IBM2000],

have been developed, there are several limitations in these commercial products. Some of them are as follows:

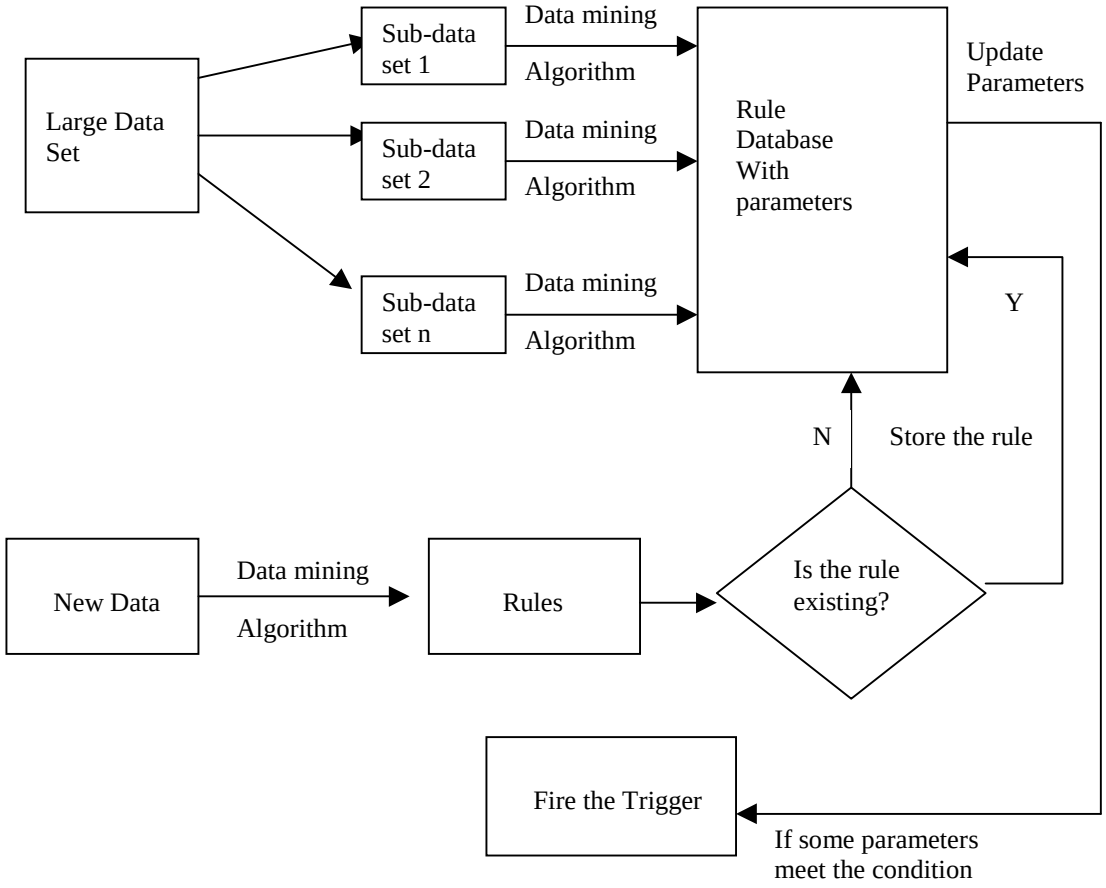


Figure 1.2 Active Data Mining

Limitation #1: The first limitation is that the existing software can not connect to multiple database management systems. These existing commercial products can use the data from the flat file, or from one specific DBMS as the input data set. For example, the Intelligent Miner can use the text file or the data stored in DB2 database as the data source. But in reality, some users may have data stored in multiple database management systems, so it is very helpful to have the mining software have this ability.

Solution: We try to address this problem using Java Database Connectivity (JDBC) so that our software can connect to different database management systems with very few extra codes.

Limitation #2: The second limitation is that most of the existing softwares use Cache-Mine architecture [THO1998]. In this architecture, the whole data set is copied to the local disk from remote database or remote flat file. Then all the computations are done in the local machine. In additional, only one algorithm is available for one mining operation.

Solution: Instead of Cache-Mine architecture, we will use another alternative SQL-based approach [THO1998] in this thesis. Six different approaches will be implemented since they have advantages as well as disadvantages for the different data sets. Three of the approaches are based purely on SQL-92 and three of them are based on SQL-OR.

Limitation #3: The third limitation is that the existing products do not provide the powerful rule visualization tools. One powerful visualization tool should have not only the good presentation method, but also a good graphic user interface to provide the user a convenient interactive environment.

Solution: We use “rule-item” relationship in the association rule visualization to replace the “item-item” relationship [SGI2000] or directed graph [IBM2000]. Java 3D, a new feature provided by JDK1.2, will be used to implement the three-dimensional display. In additional, a table format visualization module will also be implemented. For both table format and three-dimensional display, sorting and filtering functions will be

provided through the graphic user interface. It will make our visualization module easier to use.

Limitation #4: The fourth limitation is also related to the data source. Right now all the available products can only use the data from one table, but in reality, it is very common to collect the data from different tables as the input data set. So it is very useful to have the mining software to have this ability.

Solution: We will provide the user an interface to choose the tables he wants to use as the data source. For each table, the user can specify the columns that he interests. Once the system got the information, a set of JOIN/UNION operations will be applied to generate the suitable input data set.

Limitation #5: The fifth limitation is that in the existing products, all of them use only one mining algorithm. But in fact some algorithms are better than the other ones for the different kinds of input data sets. It is useful to have different algorithms available for different kinds of data sets.

Solution: We plan to implement a Mining Optimizer so that our system will have the capability to decide which one algorithm should be applied to the particular data set automatically based on the metadata of the given data set.

In this thesis, we will address the solutions of first three limitations. The solutions of limitation #4 and #5 are addressed in Mahesh's thesis [DUD2000].

1.3 Thesis Organization

The remainder of this thesis is organized as follows. In Chapter 2, we describe the architecture of JDBC, and explain how the JDBC works with different DBMSs. Some special characteristics of Oracle, such as stored procedure, will also be introduced in that

chapter. The six different association rule mining algorithms are presented in Chapter 3. In Chapter 3, we also provide the performance testing using different kinds of data sets to verify our analysis of advantage and disadvantage of each mining algorithm. Visualization of association rules is detailed in Chapter 4. In Chapter 5, we describe the major parts of the interfaces as well as the architecture of our software. Finally the conclusions and future work are in Chapter 6.

CHAPTER 2
ARCHITECTURE AND FEATURES OF JDBC AND ORACLE

In this Chapter, We begin with the introduction of the function of JDBC and the architecture of JDBC application in Section 2.1. Besides the standard SQL statements, we also use some additional features provided by the specific DBMS to improve the performance. Section 2.2 describes these specific features for Oracle.

2.1 JDBC

JDBC (Java Database Connectivity) developed by Sun [SUN2000], is a Java API for connecting to and executing SQL statements in different Database Management Systems. JDBC includes a set of classes and interfaces written in Java. They are low-level APIs, and are used to invoke SQL commands directly. There are two kinds of models for database access: two-tier and three-tire. In the two-tier model, the client makes request to a DBMS associated with the server, through JDBC by sending SQL statements to the server and when the results are ready, the server will send the results back to the client. In the Three-tier model, instead of sending the request directly to the database server, the client sends requests to an intermediate server (termed application server), which applies some business logic, and then the SQL statements are sent to the database server by the application server. Finally, the result will be returned to the client through the application server. The advantage of the Three-tier model is that the business logic can be implemented in the application server, so when the business logic changes, only the program in the application server needs to be modified accordingly, and it is not

necessary to update the program in the clients. Figures 2.1 and 2.2 show the architecture of two-tier and three-tier models, respectively. Because we are not incorporating any business logic and hence addition of a tier adds complexity without any gains for what we are trying to do, we choose the two-tier architecture for our data-mining project.

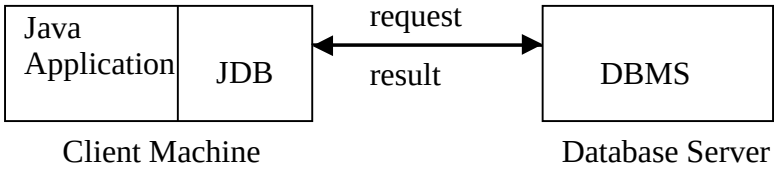


Figure 2.1 Architecture of Two-tier Model

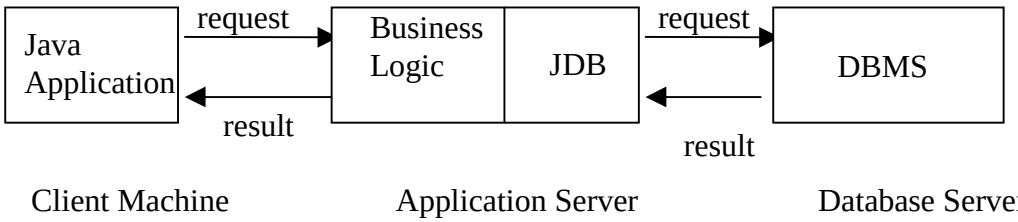


Figure 2.2 Architecture of Three-tier Model

Figure 2.3 illustrates the architecture of JDBC. It has a driver manager that is responsible for choosing JDBC driver to be used for making a connection. JDBC-ODBC bridge driver is used to use ODBC through JDBC to access some of the less popular DBMS (such as MS Access) if JDBC drivers have not been implemented for them.

The most important advantage of using JDBC compared to using ODBC is that JDBC drivers are written completely in Java, they are platform independent; ODBC is not completely platform independent and is not appropriate for direct use from Java since it uses a C interface.

2.2 Features of Oracle

In real-life scenarios, mining is typically performed on large volumes of data. Hence it is appropriate to include as much computation as possible on the server side. There are some significant advantages to perform computation inside the Server:

Executing functions inside the server means that these functions can be shared by all of the database applications, so it is not necessary to duplicate codes in each application.

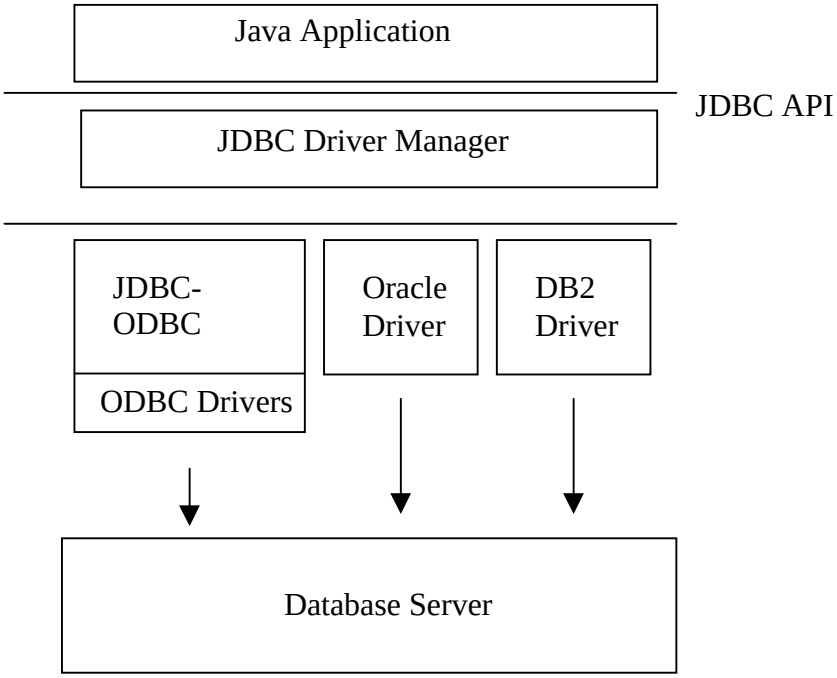


Figure 2.3 Architecture of JDBC

Execution of function inside the server can minimize the network traffic because some of the business logic can be processed in the Server, and only the results are sent back to the client. In DB2, when a UDF (User Defined Function) is created, there is an option of “FENCED” or ‘UNFENCED” modes [CHA1998]. The FENCED option

specifies that the UDF must always be run in an address space that is separate from the database, while UNFENCED option specifies that the UDF runs in the same address space as the database. FENCED option causes a performance penalty because of the process-switching when the UDF is called, but it protects the database integrity against the accidental damage that might be caused by the function. Oracle does not support this option.

Oracle provides some mechanisms, such as external procedures, and PL/SQL procedures to perform computations inside the server. Oracle supports an external procedure which uses the DLL (Dynamic Link Library) written in the host programming language such as C. However, Oracle 8.0 does not support the DLL written in Java. If we used a Java external procedure, we had to use Java Native Interface to communicate between Java and C programs, as our client is written in Java. This would be inefficient and increase the implementation effort as well.

PL/SQL stored procedure is another mechanism support by Oracle that meets our requirements. PL/SQL is a complete, block-structured programming language, and it provides some additional features that standard SQL does not have, such as loops, conditional statements, etc. Because the SQL DML (data manipulation language) can be included inside the PL/SQL stored procedure directly, the results can be saved by inserting the results into the table. This feature is different from those of DB2. DB2's table function does not create a physical table, but in Oracle, a physical table can be created and values stored in the table. Figure 2.4 illustrates the format of one PL/SQL stored procedure named 'SaveTid'. A PL/SQL stored procedure begins with the

declaration section followed by the procedure body. The actual code of SaveTid() is presented and explained in detail in Chapter 3.

```
CREATE OR REPLACE PROCEDURE SaveTid(rowCount IN INTEGER) AS
        Declaration Section
BEGIN
        Retrieve the data from source table 'TIDITEM' one row by one row using
cursor;
        Processing the data, combine 'Tid' for each same 'Item';
        Insert the values into the table 'tidT';
END;
```

Figure 2.4 PL/SQL Stored procedure "SaveTid"

Suppose there is a table TIDITEM.

Table 2.1 TIDITEM Table

Item	Tid
1	100
1	300
2	100
2	200
3	200

The purpose of stored procedure 'SaveTid' is to accept one parameter 'rowcount' of table TIDITEM. The data of table TIDITEM will be processed row by row. After processing, the Tid with the same Item will be combined together to form 'T_Tids', and the number of Tid with the same Item will be stored in 'T_cnt', and finally, the three columns 'T_item', 'T_cnt', and 'T_tids' will be inserted into table tidT. The data type CLOB (Character Large Object) is used for 'T-tids' because sometimes the length of T_tids will exceed the maximum length of VARCHAR2 and CLOB can contain up to

two gigabytes (2^{31}-1 bytes). The 'INSERT' statement in the above example will insert the following values into table tidT as shown in Table 2.2.

Table 2.2 tidT Table

T_item	T_cnt	T_tids
1	2	100, 300
2	2	100, 200
3	1	200

If table TIDITEM has millions of rows, and after processing by the stored procedure, table tidT has only 1,000 rows, the network traffic will be reduced tremendously since all of the computing work will be done inside the server machine.

CHAPTER 3
ALTERNATIVE APPROACHES TO ASSOCIATION RULE MINING

In this chapter, we begin with reviewing the related work on association rule mining algorithms and different architectural alternatives in Section 3.1. The association rule mining can be broadly divided into two phases: support counting phase and rule generation phase. In Section 3.2, we present three approaches using pure SQL92 and another three approaches using stored procedures in Oracle for the support counting phase. The algorithm for rule generation is presented in Section 3.3. In Section 3.4, we provided some performance testing using different kinds of data sets for the six approaches.

3.1 Related Work

3.1.1 Apriori Algorithm

Agrawal and Srikant [AGR1994] introduced the apriori algorithm for association rule mining with input data set from flat files. This algorithm is shown in Figure 3.1.

In Figure 3.1, line 1 is the first pass. In the first pass, first it just simply counts occurrences for each item in all the transactions, then keeps all the items whose occurrences are no less than the given minimum support. These items consist of the frequent 1-itemsets (F_1). The loop from line 2 to line 11 is called a pass. In a particular pass k, there are two phases. In the first phase, a function “apriori-gen” is used to generate the candidate itemsets C_k using the frequent itemsets F_{k-1} of the previous pass. In the second phase, all the transactions in the data set are scanned. For each transaction, a

function “subset” is called to determine the candidates in C_k that are contained in a given transaction, then the support of candidates in C_k is counted. At the end of pass k, the candidate itemsets C_k is examined to determine which of the candidates are frequent. Those candidates consist of the frequent itemsets F_k of pass k. The loop continues until F_{k-1} is empty, indicating that there is no more frequent itemsets.

The six support counting approaches and rule generation process presented in this thesis are based on the framework of the above apriori algorithm.

```
1)  F1 = {frequent 1-itemsets};
2)  for ( k=2; Fk-1<>0, k++ ) do begin
3)        Ck = apriori-gen(Fk-1);              // generate new candidate sets
4)        for all transactions t ∈ D do begin
5)              Ct = subset(Ck, t);          // find all candidate sets contained in t
6)              for all candidates c ∈ Ct do
7)                    c.count++;
8)              end
9)        end
10)       Fk = {c ∈ Ck | c.count ≥ minsup};
11)  end
12) Answer = ∪k Fk;
```

Figure 3.1 Apriori Algorithm

3.1.2 Architectural Alternatives

There are several architectural alternatives for integrating data mining with relational DBMS [THO1998]. These alternatives include Cache-Mine, SQL-based approach, and Integrated approach. In this section, we discuss these three architectures.

3.1.2.1 Cache-Mine

Figure 3.2 illustrates the architecture of Cache-Mine approach. In this architecture, the GUI resides in the client side and the mining kernel can reside in the

client side (2-tier architecture), or in the application server (3-tier architecture). When the user sends the mining request to the mining kernel, the mining kernel reads data from DBMS only once and copies the data in flat files on local disk for later use. After the mining algorithm is executed, the results will be first stored in flat files on local disk, then sent back to the database server and stored in DBMS. This architecture works very efficiently because once the data are stored on local disk, the access to the data will be very fast. One of the disadvantages is that it requires additional disk space to store the data, especially when the data set is very large.

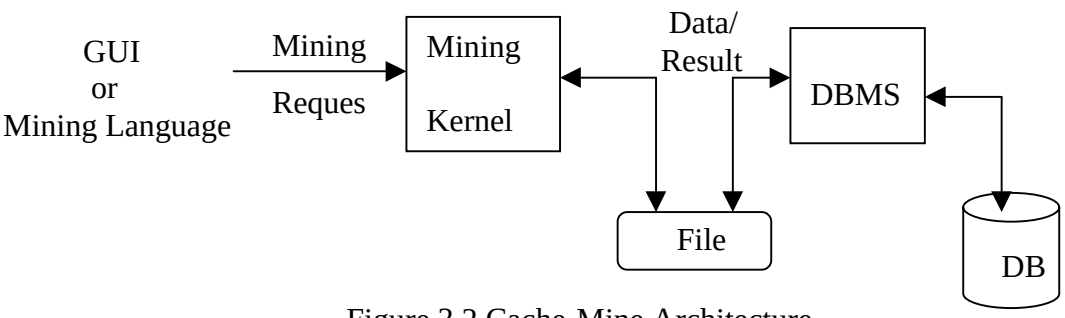


Figure 3.2 Cache-Mine Architecture

3.1.2.2 SQL-based Approach

The architecture of SQL-based approaches is illustrated in Figure 3.3. When the user specifies the mining operation, a preprocessor will generate the appropriate SQL statements for this operation. All the intermediate results are stored in the database. The SQL statements can be executed on the SQL-92 relational engine, as well as on the newer object-relational (SQL-OR) engine. SQL-OR provides some more features, such as CLOB, user-defined function, table function, stored procedure, etc. For this architecture, all the data and results are stored in the database and the data is never copied into a flat

file on the local disk. This alternative has the following advantages: (1) Additional disk space is not needed to store the data. (2) The database indexing and query processing capabilities can be exploited as much as possible. (3) The DBMS check-pointing and space management can be especially valuable for long-running mining algorithms on huge volumes of data. (4) SQL-based mining algorithm is very portable if we use only the standard SQL features. The disadvantage is that it is not as fast as Cache-Mine alternative because accessing the database generally is slower than accessing a flat file on the local disk.

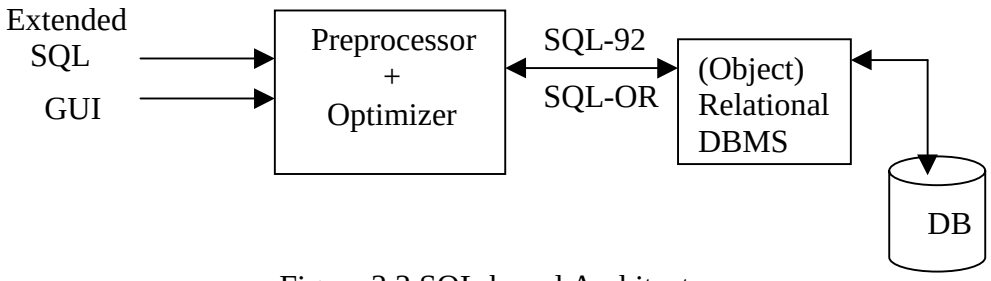


Figure 3.3 SQL-based Architecture

3.1.2.3 Integrated Approach

In the integrated approach, mining operations are integrated into the DBMS and become part of the database query engine. This approach is illustrated in Figure 3.4. In this approach, DBMS encapsulates all the detailed SQL queries for each mining operation, and gives it a new SQL command. The user can invoke the mining operation by executing the corresponding SQL command with appropriate parameters. In this case, there is no clear boundary between simple queries and mining operations to the users. All they have to do is to issue a SQL command whether it is a simple query or a mining operation. This approach is most convenient for the users.

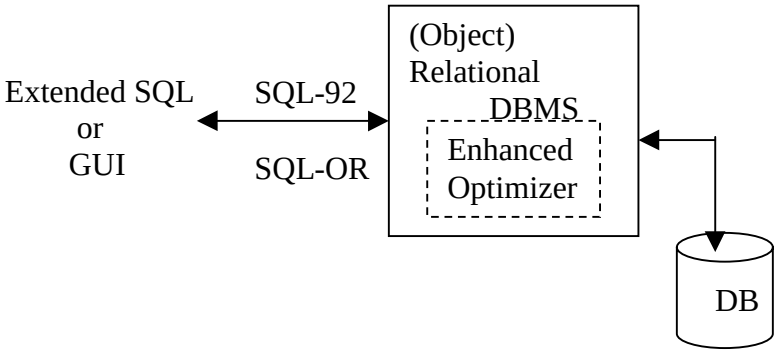


Figure 3.4 Architecture for the Integrated Approach

3.2 Support Counting

For the support counting phase, first we need to generate the candidate sets C_k for each pass k. Below, we show SQL formulations for candidate set generation.

3.2.1 Candidate Set Generation

For each pass k, C_k is a superset of the set of all frequent k-itemsets and it can be generated by F_{k-1}, which is the frequent set of the previous pass k-1. F_{k-1} has k-1 columns: $Item_1$, $Item_2$, …, $Item_{k-1}$. Because all the k-1 items in each tuple of F_{k-1} are lexicographically ordered, C_k can be obtained using the query shown in Figure 3.5.

```
Insert into Ck
        Select I1.item1, I1.item2, …, I2.itemk-1, count(*)
        From Fk-1 I1, Fk-1 I2
        Where I1.item1 = I2.item1 AND
                I1.item2 = I2.item2 AND
                        …
                        …
                I1.itemk-2 = I2.itemk-2 AND
                I1.itemk-1 < I2.itemk-1
```

Figure 3.5 SQL Query for Candidate Sets C_k

As an illustration, if F_3 is {{1, 2, 3}, {1, 2, 4}, {1, 3, 4}, {1, 3, 5}, {2, 3, 4}}, then the candidate sets of the next pass C_4 are {1, 2, 3, 4}, and {1, 3, 4, 5}.

Next, in the k-itemset of C_k, if there is any (k-1)-subset of C_k that is not in F_{k-1}, we need to delete that k-itemset from C_k. We call it "prune step". In the above example, one of the 4-itemset in C_4 is {1, 3, 4, 5}. This 4-itemset needs to be deleted because one of the 3-item subsets {3, 4, 5} is not in F_3. Because there are k subsets of length (k-1)-subset in C_k, we can do a k-way join to check if all the (k-1)-subsets are in F_{k-1}. As shown in Figure 3.5, C_k has k columns: $I_1.item_1$, I1.$item_2$, …, $I_1.item_{k-1}$, $I_2.item_{k-1}$. Since C_k is generated using the joining of two F_{k-1} tables, two (k-1)-subsets are guaranteed in F_{k-1}. We only need to check if the remaining k-2 subsets are in F_{k-1}. This can be done using additional joins by skipping one item at a time from the k-itemset. First we skip $Item_1$ and check if the subset ($I_1.item_2$, $I_1.item_3$, …, $I_1.item_{k-1}$, $I_2.item_{k-1}$) belongs to F_{k-1}, then we skip $Item_2$ to check if the subset ($I_1.item_1$, $I_1.item_3$, …, $I_1.item_{k-1}$, $I_2.item_{k-1}$) belongs to F_{k-1}. This process is repeated until $Item_{k-2}$ is reached. Figure 3.6 illustrates the join predicates. In Figure 3.6, I_1, I_2, I_3, … and I_k refer to frequent set F_{k-1}.

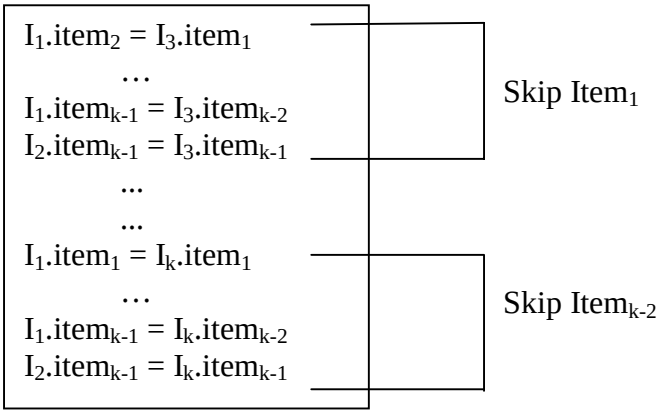


Figure 3.6 Prune step for Candidate Sets C_k

Combing Figure 3.5 and Figure 3.6, we can put the candidate sets generation and pruning step into the same query. Figure 3.7 illustrates the diagram of such a query.

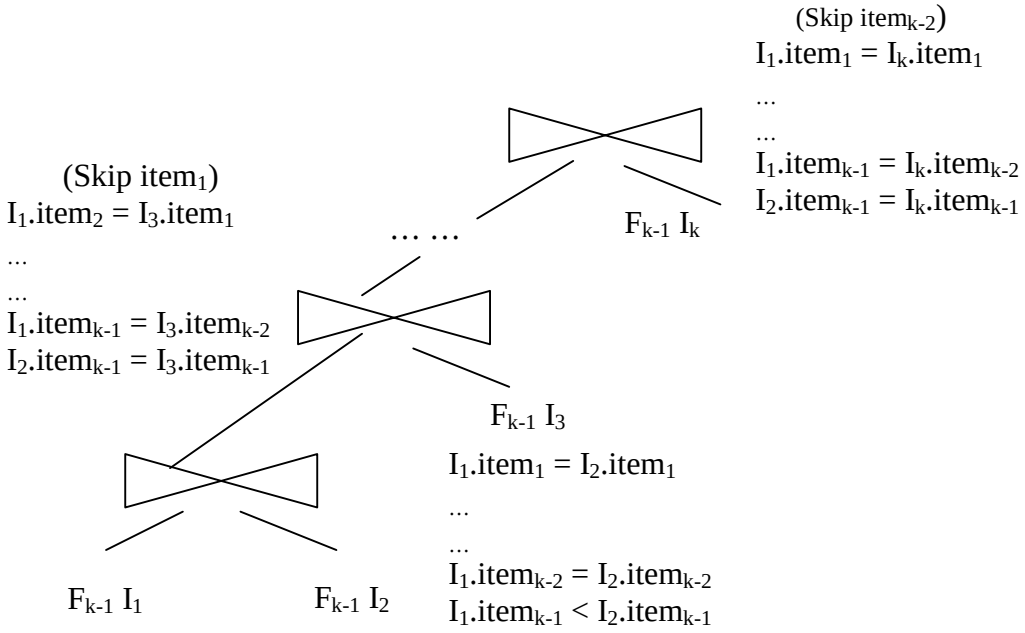


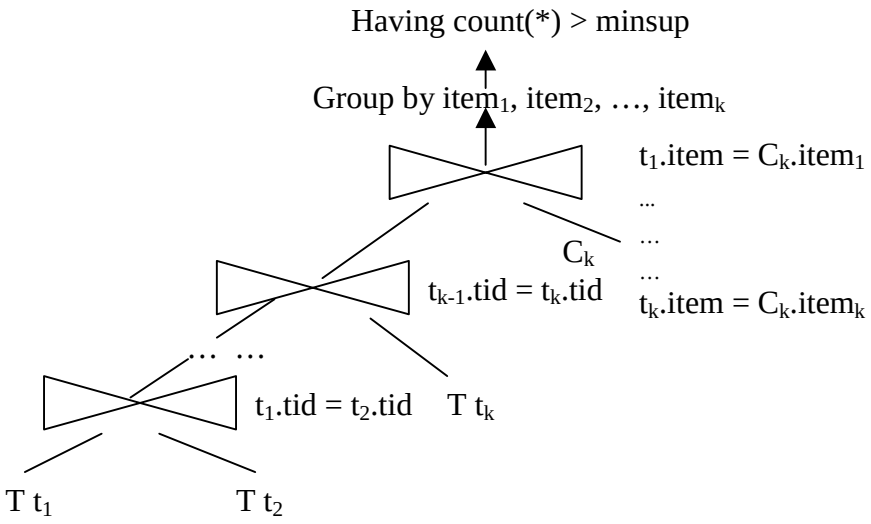
Figure 3.7 The Query of Candidate Set Generation and Pruning

3.2.2 SQL 92

In this section, we present three approaches using SQL-92, which does not include DBMS specific features, such as user defined function, stored procedure, etc.

3.2.2.1 K-Way Join

For the support counting phase, K-Way join is the most basic algorithm. In the k^{th} pass, the k input data tables are joined over the 'tid' column, and then the result is joined with the Candidate Set table C_k with the 'item' column from k tables and '$item_1$, $item_2$, …, $item_k$' from C_k. Finally, the results are grouped by $item_1$, $item_2$, …, $item_k$ and filtered by the count(*). Only the tuples that have count(*) greater than or equal to the user specified minimum support will be kept in the frequent set F_k. Figure 3.8 illustrates the query diagram and SQL query to obtain frequent set F_k for the K-Way join approach.




```
Insert into Fk
        Select item1, item2, …, itemk, count(*)
        From Ck, T t1, T t2, …, T tk
        Where t1.item = C1.item1 AND
                t2.item =  C2.item2 AND
                        …
                tk.item = Ck.itemk AND
                t1.tid = t2.tid AND
                t2.tid = t3.tid AND
                        …
                tk-1.tid = tk.tid
        Group by item1, item2, …, itemk
        Having count(*) > minsup
```

Figure 3.8 Query Diagram and SQL Query of K-Way Join

3.1.2.2 2-GroupBy

2-GroupBy is one of the algorithms to avoid multi-way joins. Figure 3.9 shows the query of 2-GroupBy. At pass k, there are two phases. In the first phase, two tables C_k and input data set T are joined based on whether the “item” of a (tid, item) pair of T is equal to any of the k items of C_k. Then the results are grouped by ($item_1$, $item_2$, …, $item_k$, tid), and only the tuples that have occurrence equal to k will be kept and stored in table

"temp". After this phase, we get all (itemset, tid) pairs that the tid supports the itemset in table "temp". In the second phase, we can simply group the item sets by ($item_1$, $item_2$, …, $item_k$) and keep only the item sets that have occurrence greater than or equal to the user specified minimum support.

Because Oracle does not support s query such as "Select * From <table name 1> As <table name 2>", we need to materialize table "temp" first in the query as shown in Figure 3.9. However, in DB2, the query for table "temp" can be nested into the second query without the need for the materialization of temp table.

```
Create Table temp AS
        Select item1, item2, …, itemk, count(*)
        From Ck, T
        Where item = Ck.item1 OR
                item =  CK.item2 OR
                        ...
                item = Ck.itemk
        Group by item1, item2, …, itemk, tid
        Having count(*) = k

Insert into Fk
        Select item1, item2, …, itemk, count(*)
        From temp
        Group by item1, item2, …, itemk
        Having count(*) > minsup
```

Figure 3.9 Query of 2-GroupBy

3.1.2.3 Sub-Query

Sub-query approach uses the common prefixes between the itemsets in the candidate sets C_k in the support counting phase. At pass k, we use a series of k sub-queries to get the frequent item set F_k. For a certain value l ($1 \leq l \geq k$), table D_l consists of the distinct itemsets formed by the first l columns of C_k. The sub-query Q_l first finds all

tids that match the distinct itemsets of D_l. Then the result is joined with the input data table T and table D_{l+1} to get Q_{l+1}. Finally, the frequent item set F_k can be get by grouping Q_k and only keep the tuples that have their occurrence greater than or equal to the user specified minimum support. Figure 3.10 illustrates the SQL query and query diagram of this approach.

```
Insert into F_k
        Select item_1, item_2, …, item_k, count(*)
        From (Subquery Q_k) t
        Group by item_1, item_2, …, item_k
        Having count(*) > minsup

Subquery Q_l (for any l between 1 and k)
        Select item_1, item_2, …, item_l, tid
        From T t_l, (Subquery Q_l-1) as R_l-1,
                (Select distinct item_1, item_2, …, item_l From C_k) as D_l
        Where R_l-1.item_1 = D_l.item_1 AND
                        …
                R_l-1.item_l-1 = D_l.item_l-1 AND
                R_l-1.tid = t_l.tid AND
                t_l.item = D_l.item_l

Subquery Q_0: No subquery Q_0
```

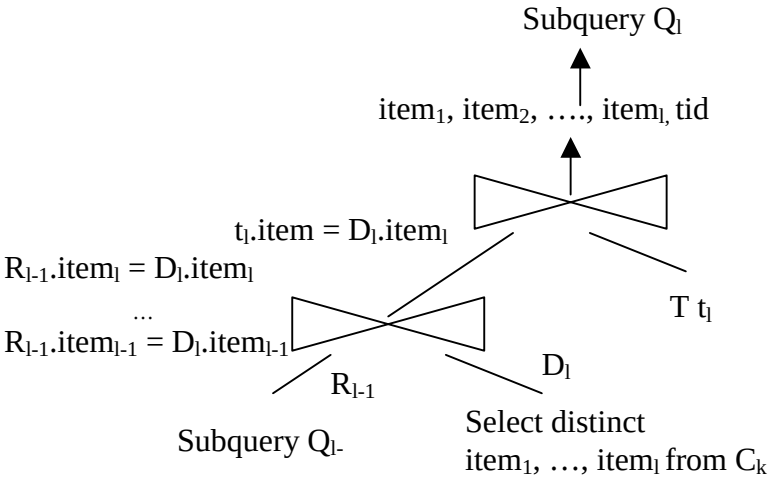


Figure 3.10 Query Diagram and SQL Query of Sub-Query

3.2.3 SQL-OR

Besides the standard SQL, each DBMS has some particular features that extend the ability of standard SQL. For example, DB2 allows the user to create "User Defined Function" (UDF) using a (host) programming language. The UDF is registered with the server and executed either within or outside the server address space (unfenced and fenced, respectively). The unfenced mode executes more efficiently than runs on the client side in the Client/Server computing environment. In Oracle, the user can define "Stored Procedure," which uses PL/SQL (Oracle's procedural extensions to SQL), as the programming language. The advantages of using stored procedure in Oracle have been listed in Chapter 2. In this section, we present three approaches using stored procedure. For DB2, we use the UDF feature for the following three approaches. The algorithms that use UDF in DB2 are presented in Mahesh's thesis [DUD2000]. The major difference of DB2 UDF and Oracle Stored procedure is that UDF uses a host programming language, while Oracle Stored procedure uses PL/SQL.

In stored procedure, the table names that are used in the stored procedure should exist when the stored procedure is compiled because Oracle checks the syntax during compiling. So we can not pass the table name as a parameter to the stored procedure. Because of this reason, we reserve "TIDITEM" as the input table name. Each time, before applying the mining algorithm, we rename the input table to "TIDITEM", then table "TIDITEM" is renamed back to the original name after the mining algorithm is finished.

3.2.3.1 Vertical

In the vertical approach, first we transfer the input data into a vertical form by creating a table "TIDT" which has three columns: ITEM, CNT and TIDS. ITEM is the

distinct item from all transactions, TIDS contains all the tids that associated with this particular item, and CNT is the number of tid for a particular item. For the sample data set mentioned in Chapter 1, the "TIDT" table has the tuples shown in Table 3.1:

Table 3.1 Table TIDT Contains All Tids and Count for Each Item

ITEM	CNT	TIDS
1	2	100, 300
2	3	200, 300, 400
3	3	100, 200, 300
4	1	100
5	3	200, 300, 400

After the input data have been transformed into the vertical form like Table 3.1, the support counting phase begins from pass 1. In each pass, the candidate sets C_k is generated. The frequent sets F_k for each pass can then be produced using C_k and tidT tables. The implementation of this approach using Oracle stored procedures is as follows.

Step 1: Transform the input data into the vertical form. The vertical form of the input data set can be obtained using a stored procedure "SaveTid", which is illustrated in Figure 3.11. This stored procedure first declares a cursor "Select tid, item From TIDITEM Order by item", then scans the declared cursor one tuple by one tuple. As shown in Figure 3.11, there are two loops. The first loop is used to count the number of transactions for each distinct item. The distinct items and the corresponding CNT are stored in the table TIDT. In the second loop, for each tuple in the cursor, it checks if the "item" is the same as the previous "item". If they are the same, the tid is adding into the column "TIDS". Otherwise, the value of "TIDS" is stored in the table TIDT for this particular item, and then reset the column "TIDS" to the value of column "tid". When finished scanning the table, the input table will be transformed into the vertical form.

```
CREATE OR REPLACE PROCEDURE SaveTid(rowCount IN INTEGER) AS
    Vtid NUMBER;        Vitem NUMBER;                   VtempItem NUMBER;
    Vcount NUMBER; Vbuffer VARCHAR2(32000); Vleng INTEGER;    Vtids CLOB;
    CURSOR c1 IS
        SELECT tid, item FROM TIDITEM order by item;
   CURSOR c2 IS
       SELECT tid, item FROM TIDITEM order by item;
BEGIN
         Vcount:=0;
         FOR emp_rec IN c1 LOOP
                  if c1%ROWCOUNT=1 then
                           VtempItem:=emp_rec.item;
                  end if;
                  Vtid :=  emp_rec.tid;
                  Vitem := emp_rec.item;
                  if Vitem=VtempItem then
                           Vcount:=Vcount+1;
                  else
                           insert into tidT1 values(VtempItem, Vcount, empty_clob());
                           VtempItem:=Vitem;
                           Vcount:=1;
                  end if;
                  if c1%ROWCOUNT=rowCount then
                           insert into tidT1 values(VtempItem, Vcount, empty_clob());
                  end if;
         END LOOP;
         FOR emp_rec2 IN c2 LOOP
                  if c2%ROWCOUNT=1 then
                           VtempItem:=emp_rec2.item;
                  end if;
                  Vtid :=  emp_rec2.tid;
                  Vitem := emp_rec2.item;
                   if Vitem=VtempItem then
                           Vbuffer:=CONCAT(RTRIM(Vbuffer), TO_CHAR(Vtid));
                           Vbuffer:=CONCAT(RTRIM(Vbuffer), ',');
                  else
                           Vleng:=LENGTH(Vbuffer);
                           select tids into Vtids from tidT1 where item=VtempItem;
                           dbms_lob.write(Vtids, Vleng-1, 1, Vbuffer);
                           update tidT1 set tids = Vtids where item=VtempItem;
                           VtempItem:=Vitem;
                           Vbuffer:='';
                           Vbuffer:=CONCAT(RTRIM(Vbuffer), TO_CHAR(Vtid));
                           Vbuffer:=CONCAT(RTRIM(Vbuffer), ',');
                  end if;
                  if c2%ROWCOUNT=rowCount then
                           Vleng:=LENGTH(Vbuffer);
                           select tids into Vtids from tidT1 where item=VtempItem;
                           dbms_lob.write(Vtids, Vleng-1, 1, Vbuffer);
                           update tidT1 set tids = Vtids where item=VtempItem;
                  end if;
         END LOOP;
END;
```

Figure 3.11 PL/SQL Stored Procedure SaveTid()

Step 2: Get the frequent set F_1 in pass 1. Because we already have the table TIDT, which contains the columns ITEM, CNT, and TIDS, it is very easy to get the frequent set F_1. We can just keep the ITEM where CNT is greater than or equal to the given minimum support. This can be done using a query "Insert into F_1 select ITEM, CNT from TIDT Where CNT>=:minsupport".

Step 3: In pass k (k>=2), get the candidate set C_k. Table C_k has k columns $item_1$, $item_2$, …, $item_k$. It can be obtained using the method described in Section 3.1

Step 4: In pass k (k>=2), get the frequent set F_k. For the support counting, we need to get the occurrence of each tuple in C_k. After we have the table "TIDT", we can obtain the occurrence of "$item_1$, $item_2$, …, $item_k$" by counting the number of tids in the intersection of these items. In this example (Table 3.1), for the item set "2, 3", the common tids of the items "2" and "3" are "200", and "300", so the number of common tids is 2. Therefore, the support of item set "2, 3" is 2. We created a series of stored procedures "$CountAnd_k$" for this task. The stored procedure "$CountAnd_k$" takes k parameters (each parameter is a tid-list), and return the number of common tids among these k tids. . Figure 3.12 illustrates the stored procedure "$CountAnd_2$". "$CountAnd_2$" first read the two tid-lists into two arrays, then the number of common tids among these two tid-lists can be obtained by scanning these two arrays. We can apply the stored procedure "$CountAnd_k$" for each tuple in C_k to get the number of common tid for each item set. The item sets C_k can be expanded to the frequent sets F_k by adding the support count for each tuple into the table C_k and then delete the tuples whose support count is less than the user specified minimum support.

```
CREATE OR REPLACE FUNCTION countAnd2(in1 CLOB, in2 CLOB) RETURN NUMBER IS returnCount
NUMBER;

  TYPE vType IS VARRAY(10000) OF VARCHAR2(50);
  v1          vType;  v2 vType;   pos1          INTEGER;  pos2       INTEGER;  item       VARCHAR2(20);
  curChar CHAR(1);  patt          VARCHAR2(10);   len           INTEGER;  clob1Len  INTEGER;
  clob2Len  INTEGER;  loopCount          INTEGER;  lastItem   INTEGER;
BEGIN
  returnCount:=0;
-- initialize the varrays
  v1:=vType(NULL);
  v2:=vType(NULL);
  patt:=',''; -- pattern i s ','
  clob1Len := DBMS_LOB.GETLENGTH(in1);  --get the clob1 length
  item:='';
  loopCount:=0;
--  dbms_output.put_line('Varray 1');
  FOR i IN 1..clob1Len LOOP
    curChar:=DBMS_LOB.SUBSTR(in1,1,i);
    IF curChar=patt THEN
                loopCount:=loopCount+1;
                v1(loopCount):=item;
                v1.extend;
                item:='';
--        dbms_output.put_line('v1('||loopCount|| ') : ' || v1(loopCount));
    ELSE
                item:=item || curChar;
    END IF;
  END LOOP;
  loopCount:=loopCount+1;
  v1(loopCount):=item;
--  dbms_output.put_line('v1('||loopCount|| ') : ' || v1(loopCount));
----------Till here for VARRAY v1
  clob2Len := DBMS_LOB.GETLENGTH(in2);  --get the clob1 length
  item:='';
  loopCount:=0;
--  dbms_output.put_line('Varray 2');
  FOR i IN 1..clob2Len LOOP
    curChar:=DBMS_LOB.SUBSTR(in2,1,i);
    IF curChar=patt THEN
                loopCount:=loopCount+1;
                v2(loopCount):=item;
                v2.extend;
                item:='';
--        dbms_output.put_line('v2('||loopCount|| ') : ' || v2(loopCount));
    ELSE
                item:=item || curChar;
    END IF;
  END LOOP;
  loopCount:=loopCount+1;
  v2(loopCount):=item;
--  dbms_output.put_line('v2('||loopCount|| ') : ' || v2(loopCount));
----------Till here for VARRAY v2
-- now have to loop till the end of the arrays and meanwhile count the common items.
  clob1Len := v1.COUNT;
  clob2Len := v2.COUNT;
  FOR i IN 1..clob1Len LOOP
                FOR j IN 1..clob2Len LOOP
                        IF v1(i)=v2(j) THEN
                                returnCount:=returnCount+1;
                        END IF;
                END LOOP;
  END LOOP;
  return (returnCount);
END;
```

Figure 3.12 Stored Procedure $CountAnd_2()$

3.2.3.2 GatherJoin

The GathoerJoin approach first transer the input data into a vertical form by creating a table “TITEM” which has three columns: TID, CNT and ITEMS. TID contains the distinct tids in all transactions. ITEMS contain all the items that belong to a particular tid. CNT is the number of items for the particular tid. The table TIETM created from the example input data set is shown in Table 3.2.

Table 3.2 Table TITEM Contains All Items and Count for each Tid

TID	CNT	ITEMS
100	3	1, 3, 4
200	3	2, 3, 5
300	4	1, 2, 3, 5
400	2	2, 5

After the input data has been transformed into the vertical form like Table 3.2, the support counting phase begins from pass 1. In each pass, the candidate sets C_k is not needed because we already have the table TITEM. The frequent item sets F_k can be produced based purely on table TITEM. The implementation of this approach using Oracle stored procedures is as follows.

Step 1: Transform the input data into the vertical form. The vertical form of the input data set can be obtained using a stored procedure “SaveItem”, which is shown in Figure 3.13. This stored procedure first declares a cursor “Select tid, item From TIDITEM Order by tid”, then scans the declared cursor one tuple by one tuple. As shown in Figure 3.13, there are two loops. The first loop is used to count the number of items for each distinct transaction. The distinct transactions and the corresponding CNT are stored in the table TITEM.

```
CREATE OR REPLACE PROCEDURE SaveItem(rowCount IN INTEGER) AS
        Vtid NUMBER;  Vitem NUMBER; VtempTid NUMBER;     Vcount NUMBER;
        Vbuffer VARCHAR2(32000);      Vleng INTEGER;          Vitems CLOB;
        CURSOR c1 IS
            SELECT tid, item FROM TIDITEM order by tid;
        CURSOR c2 IS
            SELECT tid, item FROM TIDITEM order by tid;
BEGIN
        Vcount:=0;
        FOR emp_rec IN c1 LOOP
                if c1%ROWCOUNT=1 then
                        VtempTid:=emp_rec.tid;
                end if;
                Vtid :=  emp_rec.tid;
                Vitem := emp_rec.item;
                 if Vtid=VtempTid then
                        Vcount:=Vcount+1;
                else
                        insert into titem1 values(VtempTid, Vcount, empty_clob());
                        VtempTid:=Vtid;
                        Vcount:=1;
                end if;
                if c1%ROWCOUNT=rowCount then
                        insert into titem1 values(VtempTid, Vcount, empty_clob());
                end if;
        END LOOP;
        FOR emp_rec2 IN c2 LOOP
                if c2%ROWCOUNT=1 then
                        VtempTid:=emp_rec2.tid;
                end if;
                Vtid :=  emp_rec2.tid;
                Vitem := emp_rec2.item;
                 if Vtid=VtempTid then
                        Vbuffer:=CONCAT(RTRIM(Vbuffer), TO_CHAR(Vitem));
                        Vbuffer:=CONCAT(RTRIM(Vbuffer), ',');
                else
                        Vleng:=LENGTH(Vbuffer);
                        select items into Vitems from titem1 where tid=VtempTid;
                        dbms_lob.write(Vitems, Vleng-1, 1, Vbuffer);
                        update titem1 set items = Vitems where tid=VtempTid;
                        VtempTid:=Vtid;
                        Vbuffer:='';
                        Vbuffer:=CONCAT(RTRIM(Vbuffer), TO_CHAR(Vitem));
                        Vbuffer:=CONCAT(RTRIM(Vbuffer), ',');
                end if;
                if c2%ROWCOUNT=rowCount then
                        Vleng:=LENGTH(Vbuffer);
                        select items into Vitems from titem1 where tid=VtempTid;
                        dbms_lob.write(Vitems, Vleng-1, 1, Vbuffer);
                        update titem1 set items = Vitems where tid=VtempTid;
                end if;
        END LOOP;
END;
```

Figure 3.13 Oracle Stored Procedure SaveItem()

In the second loop, for each tuple in the cursor, it checks if the “tid” is the same as the previous “tid”. If they are the same, the item is adding into the column “ITEMS”. Otherwise, the value of “ITEMS” is stored in the table TITEM for this particular tid, and then reset the column “ITEMS” to the value of column “item”. When finished scanning the table, the input table will be transformed into the vertical form.

Step 2: Get the frequent set F_1 in pass 1. The frequent set F_1 can be obtained by querying the input table TIDITEM. We just keep the items that the occurrence is greater than or equal to the given minimum support. The query “Insert into F_1 Select item, count(*) from TIDITEM Group by item Having count(*)>=:minsupport” should do it.

Step 3: In pass k (k>=2), get the frequent set F_k. Once we got the TITEM table, we have stored all the items which has the same tid into one column (ITEMS). For the support counting in pass k, we have a series of stored procedures “$Comb_k$” to find all the k-item combinations of items in the column ITEMS. For example, for the third row of Table 3.2 (TID=300), at pass 3, the stored procedure “$Comb_3$” generates the following combinations: {1,2,3}, {1,2,5}, {1,3,5}, and {2,3,5}. Figure 3.14 shows stored procedure “$Comb_2$”, which takes one parameter (item-list) and generates all the 2-item combinations of items in the column ITEMS. As shown in Figure 3.14, it first reads the item-list into an array, and then the 2-item combinations of items can be obtained by scanning the array. In pass k, each tuple of table TITEM is processed using the stored procedure “$Comb_k$” and the generated k-item combinations are stored in a table TT_k which has k columns: T_item_1, T_item_2, …, T_item_k. Finally, the support of each k-item combination can be obtained easily by using the “Group By” query and the frequent item

sets F_k can be obtained by deleting all the tuples that has support less than the user specified minimum support. The SQL syntax for this task is listed in Figure 3.15.

```
CREATE OR REPLACE PROCEDURE Comb2(in1 NUMBER, in2 CLOB) AS

  TYPE vType IS VARRAY(10000) OF VARCHAR2(50);
  v1        vType;
  pos1     INTEGER;  pos2 INTEGER;  item VARCHAR2(20);  curChar CHAR(1);
  patt      VARCHAR2(10);   len    INTEGER;  clob1Len       INTEGER;  loopCount      INTEGER;
BEGIN
-- initialize the varrays
  v1:=vType(NULL);

  patt:=',''; -- pattern i s ','

  clob1Len := DBMS_LOB.GETLENGTH(in2);  --get the clob1 length

  item:='';
  loopCount:=0;
--  dbms_output.put_line('Varray 1');
  FOR i IN 1..clob1Len LOOP
    curChar:=DBMS_LOB.SUBSTR(in2,1,i);
    IF curChar=patt THEN
            loopCount:=loopCount+1;
            v1(loopCount):=item;
            v1.extend;
            item:='';
--        dbms_output.put_line('v1('||loopCount|| ') : '|| v1(loopCount));
    ELSE
            item:=item || curChar;
    END IF;
  END LOOP;
  loopCount:=loopCount+1;
  v1(loopCount):=item;
--  dbms_output.put_line('v1('||loopCount|| ') : '|| v1(loopCount));
-----------Till here for VARRAY v1

  clob1Len:=v1.COUNT;

  FOR i IN 1..clob1Len-1 LOOP
            FOR j IN i+1..clob1Len LOOP
              INSERT INTO T_COMB2 VALUES(v1(i), v1(j));
            END LOOP;
  END LOOP;
  END;
```

Figure 3.14 Oracle Stored Procedure $Comb_2()$

```
Insert into Fk
        Select T_item1, T_item2, ..., T_itemk, count(*)
        From TTk
        Group by T_item1, T_item2, …, T_itemk
        Having count(*) >= minimun support
```

Figure 3.15 Support Counting of GathorJoin

3.2.3.3 GatherJoin Variant

In Gather Join Variant approach, similar to GatherJoin approach, we first transform the input data into the vertical form. However, this approach uses the candidate sets C_k in each pass k for support counting phase. The implementation of this approach using Oracle stored procedures is as follows.

Step 1: Transform the input data into the vertical form. This step is to transform the input data from the format of "TID, ITEM" into the format of "TID, CNT, ITEMS". The same stored procedure "SaveItem", which is described in detail in GatherJoin approach, is used to complete this task. After transforming, a table TITEMS that has three columns "TID, CNT, ITEMS" is produced.

Step 2: Get the frequent set F_1 in pass 1. This step is also the same as step 2 in GatherJoin approach. The query "Insert into F_1 Select item, count(*) from TIDITEM Group by item Having count(*)>=:minsupport" will get all the frequent items in pass 1.

Step 3: In pass k (k>=2), get the candidate sets C_k. The candidate sets C_k is slightly different than those used in the other approaches. In this approach, table C_k has a unique identifier for each tuple. So C_k has k+1 columns: oid, $item_1$, $item_2$, …, $item_k$ where oid is the unique identifier for each tuple. To get C_k, first we use the same algorithm described in Section 3.2.1 (Candidate Set Generation) to generate the candidate

sets, then we use the stored procedure "CreateC_k" to add one column "oid" into the candidate sets. "oid" will be filled with the unique number begin with 1.

Step 4: In pass k (k>=2), get the frequent sets F_k. After we get C_k, we create an index "Cind" on table C_k based on column "oid". For each tuple in table TITEM, the k-item combination subset of column ITEMS are generated and stored in table TT_k using the same stored procedures "$Comb_k$" described in the GatherJoin approach. Then one table $TEMP_k$ is created and populated by joining two tables C_k and TT_k. Finally the frequent item sets F_k can be obtained by joining tables C_k and $TEMP_k$ based on column "oid". Figure 3.16 illustrates the SQL query of how to get table $TEMP_k$ and F_k.

```
Insert into TEMPk
        Select oid, count(*)
        From Ck, TTk
        Where item1 = T_item1
            And item2 = T_item2
                        …
                        …
             And itemk = T_itemk
        Group by oid
        Having count(*) >= minimun support

Insert into Fk
        Select item1, item2, ..., itemk, cnt
        From Ck, TEMPk,
        Where TEMPk.oid = Ck.oid
```

Figure 3.16 Support Counting of GathorJoin Variant

3.3 Rule Generation

3.3.1 Intermediate Rule Generation

After the support counting phase is finished, all the frequent item sets were stored in the tables Fx (F_1, F_2, F_3, etc), where 'x' denotes the pass number. To generate the rules, first all the records in these tables are combined together to form a new table called 'FISETS' (Frequent ItemSets). So the table 'FISETS' has the format of ($ITEM_1$, $ITEM_2$, $ITEM_3$, …, $ITEM_k$, NULLM, COUNT). Table 3.3 shows one example of 'FISETS'.

Table 3.3 Frequent Item Sets Table 'FISETS'

$ITEM_1$	$ITEM_2$	$ITEM_3$	$ITEM_4$	$ITEM_5$	$ITEM_6$	$ITEM_7$	$ITEM_8$	NULLM	COUNT
1	0	0	0	0	0	0	0	2	2
2	0	0	0	0	0	0	0	2	3
3	0	0	0	0	0	0	0	2	3
5	0	0	0	0	0	0	0	2	3
1	3	0	0	0	0	0	0	3	2
2	3	0	0	0	0	0	0	3	2
2	5	0	0	0	0	0	0	3	3
3	5	0	0	0	0	0	0	3	2
2	3	5	0	0	0	0	0	4	2

In Table 3.3, 'NULLM' indicates 'null mark', and 'COUNT' indicates the number of items. For example, the last row means that item 2, 3, and 5 appear together for 2 times.

For each row in FISETS, we need to find all the non-empty subsets using the format of 'rule head => rule body'. One example is that for the items '2, 3, 5', all the non-empty subsets are: 2 => 3, 5; 3 => 2, 5; 5 => 2, 3; 2, 3 => 5; 2, 5 => 3 and 3, 5 => 2. For the rows of Table 3.3, the GenSubSets function generates the table Primary-Rules, which is shown in Table 3.4.

TNULLM has the same mean as ‘NULLM’ in table ‘FISETS’. TRULEM means ‘rule null mark,’ which is the position of beginning of rule body. For example, the first row in Table 3.4 indicates the rule 1 => 3 with support 2 and the last row indicates the rule 3, 5 => 2 with support 2.

Table 3.4 Table ‘Primary-Rules’

$TITEM_1$	$TITEM_2$	$TITEM_3$	$TITEM_4$	$TITEM_5$	$TITEM_6$	$TITEM_7$	$TITEM_8$	TNULLM	TRULEM	TCOUNT
1	3	0	0	0	0	0	0	3	2	2
3	1	0	0	0	0	0	0	3	2	2
2	3	0	0	0	0	0	0	3	2	2
3	2	0	0	0	0	0	0	3	2	2
2	5	0	0	0	0	0	0	3	2	3
5	2	0	0	0	0	0	0	3	2	3
3	5	0	0	0	0	0	0	3	2	2
5	3	0	0	0	0	0	0	3	2	2
2	3	5	0	0	0	0	0	4	2	2
3	2	5	0	0	0	0	0	4	2	2
5	2	3	0	0	0	0	0	4	2	2
2	3	5	0	0	0	0	0	4	3	2
2	5	3	0	0	0	0	0	4	3	2
3	5	2	0	0	0	0	0	4	3	2

Because table primary-rules already includes all the rules with the minimum support, to get the rules with minimum confidence, we only need to join the table ‘FISETS’ and ‘Primary-Rules.’ According to the definition of confidence:

$$Confidence = \frac{The\ Number\ Of\ Transaction\ That\ Contains\ Y}{The\ Number\ Of\ Transaction\ That\ Contains\ X}$$

where X means rule head, and Y means rule body. For each row in table Primary-Rules, we need to find the same rule head from table ‘FISETS,’ and then divide the support by the corresponding support from table ‘FISETS.’ Again for the last row in table ‘Primary-Rules,’ 3, 5 => 2 with support 2, we can find from the ‘FISETS’ that the support with

item ‘3, 5’ is 2, so the confidence of rule ‘3, 5 => 2’ is 2/2=100%. Figure 3.17 is the join query to accomplish this task.

```
Insert into Rules
        Select TITEM1, TITEM2, …, TITEMk, TNULLM, TRULEM,
                TCOUNT,   (TCOUNT/COUNT)*100
        From Primary-Rules t1, FISETS t2
        Where  (t1.titem1 = t2.item2 or t1.TRULEM<=1) AND
                (t1.titem2 = t2.item3 or t1.TRULEM<=2) AND
                                …
                 (t1.titemk= t2.itemk or t1.TRULEM<=k) AND
                 t1.TRULEM = t2.NULLM AND
                (TCOUNT/COUNT)*100 >= min confidence
```

Figure 3.17 Association Rules Generation Query

Table 3.5 shows all the rules that has the confidence >=50%.

Table 3.5 Table ‘Rules’

$ITEM_1$	$ITEM_2$	$ITEM_3$	$ITEM_4$	$ITEM_5$	$ITEM_6$	$ITEM_7$	$ITEM_8$	NULLM	RULEM	CONF	SUP
1	3	0	0	0	0	0	0	3	2	100	50
3	1	0	0	0	0	0	0	3	2	66.67	50
2	3	0	0	0	0	0	0	3	2	66.67	50
3	2	0	0	0	0	0	0	3	2	66.67	50
2	5	0	0	0	0	0	0	3	2	100	75
5	2	0	0	0	0	0	0	3	2	100	75
3	5	0	0	0	0	0	0	3	2	66.67	50
5	3	0	0	0	0	0	0	3	2	66.67	50
2	3	5	0	0	0	0	0	4	2	66.67	50
3	2	5	0	0	0	0	0	4	2	66.67	50
5	2	3	0	0	0	0	0	4	2	66.67	50
2	3	5	0	0	0	0	0	4	3	100	50
2	5	3	0	0	0	0	0	4	3	66.67	50
3	5	2	0	0	0	0	0	4	3	100	50

3.3.2 Mapping Back Process

In the real data set, each item usually is represented by an understandable name (such as bike, helmet, etc). However, compared to integer representation, text representation takes more space and computation. Also, most of the algorithms used, assume lexicographic ordering of items which is also straightforward in integer representation. Hence, we use integers for internal representation and computing and when the rules are generated, these integers are mapping back to the original name. This task can be done by creating a "description" table. When we get the input data set, the distinct items are selected, and each of them is assigned an integer number begin with 1. The integer number can be incremented by 1 for each distinct item. So the table named "description" can be constructed like the format in Table 3.6.

Table 3.6 Example of "Description" Table

Description	**Item Number**
Bike	1
Helmet	2
Battery	3
Milk	4
Eggs	5
…	…
…	…

After the intermediate rules are generated (shown in Table 3.5), the final rule table can be produced by joining the intermediate rule table and the "description" table. Finally the rules will be presented by the following rule format:

Rule Head	=>	Rule Body	Confidence	Support

The items can be put in rule head or rule body by checking the value of "NULLM" and "RULEM" columns of each rule.

3.4 Performance Testing

The performance testing of these six approaches use the synthetic generated data sets with different size. The description of these data sets is detailed in Section 3.4.1. In Section 3.4.2, we compare the performance of SQL-92 and SQL-OR approaches with Intelligent Miner. Scale-Up experiments are conducted with various sized data sets in Section 3.4.3. All the experiments are conducted on IBM DB2 Universal (Version 5) installed on Window NT Server with 2 processors, 256 MB main memory, and 12 GB disk. For all the experiments, the minimum confidence is kept as a constant 50%. We run 3 times for each dataset/approach/support combination and take the average time of the last 2 run as the average run time for this combination.

3.4.1 Synthetic Data Generation

We use the synthetic data generator from IBM to generate various data sets. This data generator provides some options to generate different size of data sets. Some of the options that we used are:

- -ntrans <number_of_transactions> (in 1000's) (default: 1000)
- -tlen avg_items_per_transaction (default: 10)
- -nitems number_of_different_items (in '000s) (default: 100000)
- -fname <filename> (write to filename.data and filename.pat)

We vary these options to generate different kinds of data sets that are listed in Table 3.7. For example, if we want to have a data set with the following parameters:

- 200K transactions

- The average number of items in one transaction is 5
- The number of different items is 1000
- The data set is stored in file T5D200K.data

We can use the following command:

gen lit –ntrans 200 –tlen 5 –nitems 1 –fname T5D200K

Table 3.7 Synthetic Data Sets

Data Sets	Number of Records	Number of Transactions	Average Number of Items Per Transaction
T5D1K	5,605	1,000	5
T5D10K	54,948	10,000	5
T5D100K	547,282	100,000	5
T10D10K	105,369	10,000	10

In Table 3.7, we name the data sets using the following format: T_mD_n where *m* means "the average number of items per transaction," and *n* means "the number of transactions". For example, data set "T10D10K" means this data set has 10,000 transactions and the average number of items is 10. The number of different items in all of these data sets is $k = 1000$. Usually $k >> m$, otherwise most of the transactions will have the similar items.

3.4.2 Performance of SQL-92 and SQL-OR Approaches and Intelligent Miner

Three data sets T5D10K, T5D100K, and T10D10K were used to test the run time of these approaches and Intelligent Miner with respect to four different minimum support values 0.2%, 0.15%, 0.10% and 0.05%. The experiment results of these three data sets are shown in Figure 3.18, Figure 3.19 and Figure 3.20 respectively. From these three figures, we can make the following observations.

- The performance of Kway Join and Subquery are close when the minimum support value is relatively larger. When the minimum support decreases, Subquery is worse than Kway Join.
- 2-Groupby is the worst among all the SQL approaches. Even for the data set T5D10K with support of 0.2%, it can not finish in 5 hours.
- Based purely on performance, Intelligent Miner is better than SQL approaches. This is because Intelligent Miner is based on "Cache-Mine" architecture and it copies all the data from database into the local disk when the mining begins. Once the data are in the local disk, all the computations are local.

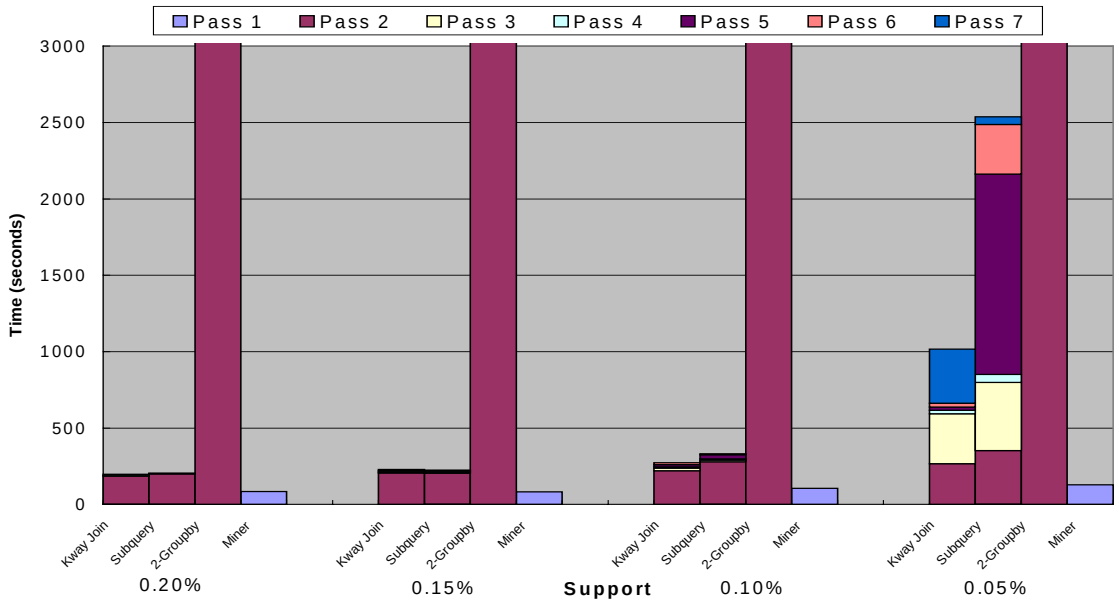


Figure 3.18 Performance Comparison of SQL-92 Approaches and Intelligent Miner for Data Set T5D10K

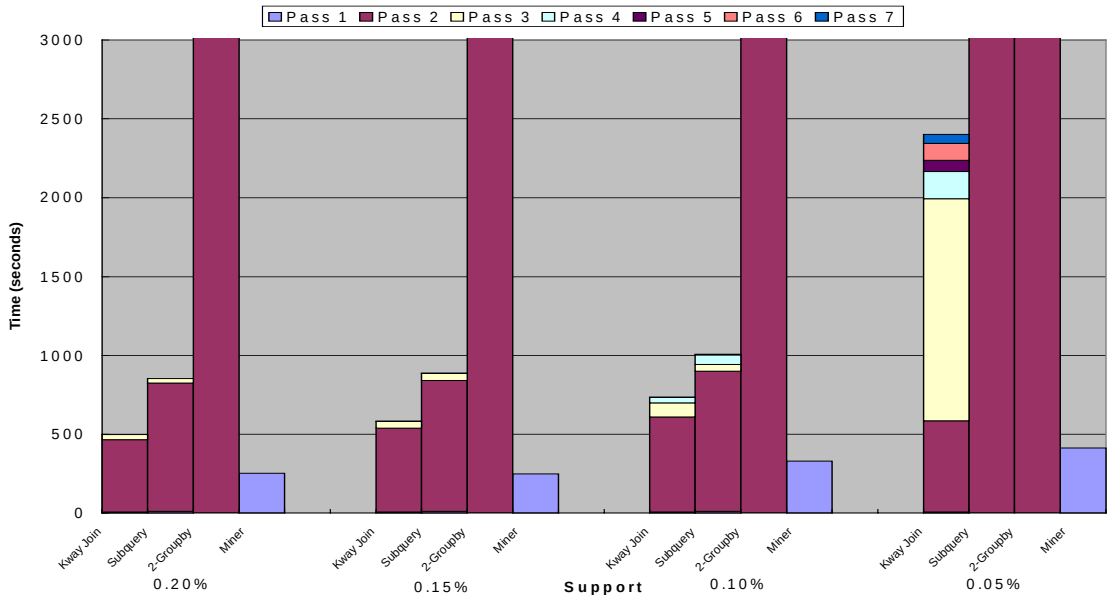


Figure 3.19 Performance Comparison of SQL-92 Approaches and Intelligent Miner for Data Set T5D100K

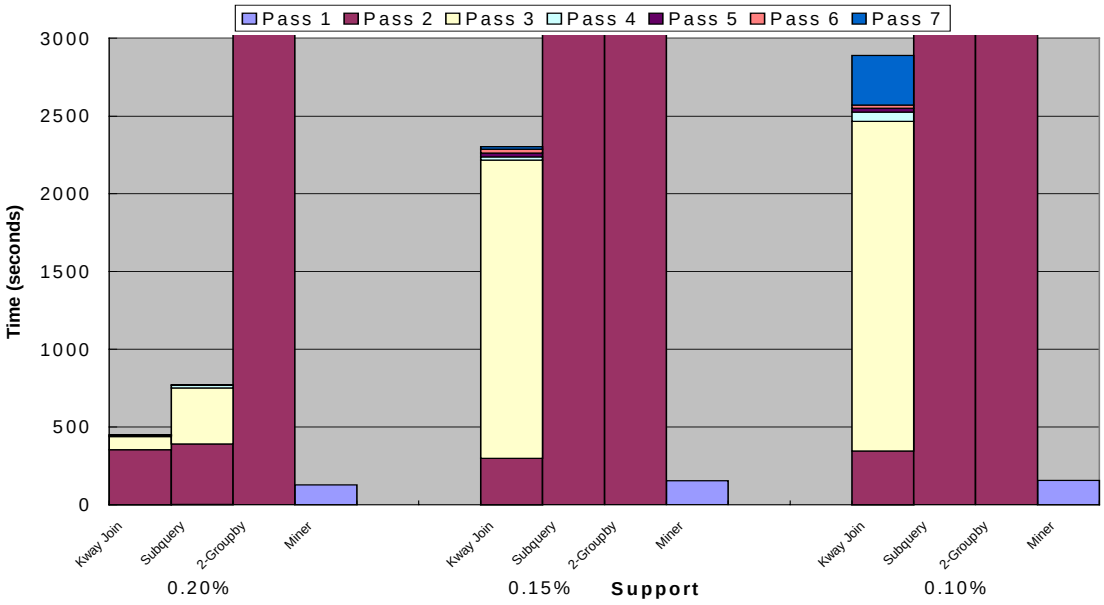


Figure 3.20 Performance Comparison of SQL-92 Approaches and Intelligent Miner for Data Set T10D10K

3.4.3 Scale-Up Experiments

We used different synthetic generated data sets to study the scale-up behavior SQL approaches with respect to increasing number of records. We varied the number of records using the different number of transactions and the average number of items per transaction. Figure 3.21 shows how these SQL approaches scales up as the number of records is increased from 5K to 500K. The minimum support and confidence values are constant for all the four data sets, which are 0.2% and 50% respectively.

From Figure 3.21 we observed that run time scale quite linearly as the number of records increased. It also shows that both Kway Join and Subquery approaches have the similar scale-up behavior. The 2-Groupby approach has not been included in Figure 3.21 because it can not complete even the smallest data sets T5D1K in 2-3 hours.

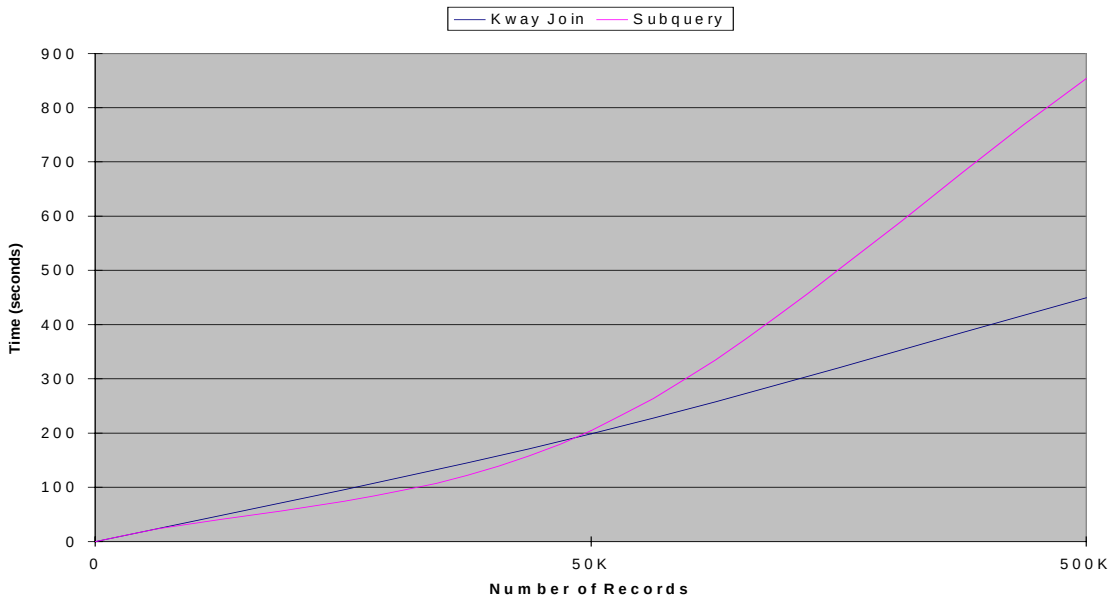


Figure 3.21 Scale-Up Experiments for SQL-92 Approaches

CHAPTER 4
VISUALIZATION OF ASSOCIATION RULES

Visualization is the process of transforming data, information, and knowledge into visual form making use of human's natural visual capabilities [GER1998]. There are three kinds of visualization categories in data mining [GRI1995]. The first approach is to use visualization techniques to present the information obtained from mining the data in the database, and this approach is conventionally being used in many data mining tools. The second approach is to visualize the data in database before applying the data mining algorithms. By using this approach, the user can have a better understanding of the data. The third approach is to use visualization techniques to complement the data mining techniques. It is also known as visual data mining allowing user to understand the data mining process and the data mining models being used. In this chapter, we will focus on the first approach by reviewing the related work of visualization in data mining, then we provide our design of rule table and 3-D rule visualization system for association rule.

4.1 Related Work

In this section, we first summarize the different categories of data visualization techniques for data mining, then visualization techniques for association rule will be reviewed.

4.1.1 Classification of Data Visualization Techniques

Data visualization techniques can be classified into five categories: (1) geometric techniques, (2) icon-based techniques, (3) pixel-oriented techniques, (4) hierarchical techniques, and (5) graph-based techniques [KEI1996].

Geometric technique is the visualization of geometric transformations and projections of data. The examples of this technique include Scatter-plot matrices, Landscapes, Projection Pursuit techniques, Prosection views, Hyperslice, and Parallel Coordinates. Icon-based technique, also known as iconic display technique, is the visualization of data values as features of icons by mapping each multidimensional data item to an icon. Examples of this technique include Chernoff Faces, Stick Figures, Shapping Coding, Color Icons, and TileBars. Pixel-oriented technique is used to represent each attribute values of a data item as a colored pixel and display the attribute values belonging to one data item in separate windows. There are two groups for this technique: Query-independent and Query-dependent technique. Query-independent technique usually is used to visualize large data sets that have natural ordering based on some attributes (i.e., time series data), while Query-dependent technique is used to visualize the relevance of the data items with respect to a query for interactive exploration.

Hierarchical technique is typically used for the visualization of data using a hierarchical partitioning of k-dimension space into 2D or 3D subspaces. Dimensional Stacking, Worlds-within-Worlds (n-Vision), Tree-map, Cone Trees, and InfoCube are some examples of this technique. Graph-based technique is to utilize large graphs to convey the meaning and structure of the data sets clearly and effectively. The graphs used

can be 2D-graph or 3D-graph, depends on the needs of the application. Because of the nature of association rule, graph-based technique is most suitable.

4.1.2 Rule Table

The most straightforward method for the association rule visualization is to use the rule table. The following rule table format has been used [THO1998]:

Item1	Item2	Item3	Item4	Item5	Item6	Item7	Item8	NullM	RuleM	Confidence	Support

Here Item1, Item2, …, and Item8 mean the 8 items, NullM means the null mark of the rule, if there are *n* items in one rule, the value of NullM should be *n+1*. RuleM means the rule mark of the rule, if there are *m* items in the rule head, the value of RuleM should be *m+1*. An example of this rule table format is illustrated in Table 4.1.

Table 4.1 Example of Association Rules in Rule Table Format

Bread	Milk	Null	Null	Null	Null	Null	Null	2	1	90%	10%
Eggs	Bread	Milk	Null	Null	Null	Null	Null	3	1	85%	7%
Bike	Pumper	Lock	Null	Null	Null	Null	Null	3	2	80%	5%
Bike	Pumper	Lock	Helmet	Null	Null	Null	Null	4	2	60%	3%

In Table 4.1, rule #3 (the third row), the column ‘NullM=3’ means the rule consists of 3 items. ‘RuleM=2’ means there are 2 items in the rule head. ‘Null’ is used to fill the rest of columns. So the third row means the association rule ‘Bike, Pumper => Lock’ with confidence of 80% and support of 5%.

4.1.3 2-D and 3-D Rule Visualization

Rule table is the most straightforward way to show the association rule to the users. However, the rule table is only suitable to display the limited number of rules to

the users. If the user needs to have a global view of all the rules, the rule table is not a suitable approach.

Several commercial data mining products provide a visualization module. Becker [BEC1998] presented a technique to visualize the decision table classifiers. In this visualization module, the interactive drill down, drill-up, drill-through, filtering, and animation gave the user more flexibility.

As to association rule visualization, lots of work has been done using directed graph, 2-D matrix, and 3-D visualization.

4.1.3.1 Directed Graph

Directed Graph is used as the association rule visualization technique in the IBM's data mining software "Intelligent Miner". In directed graph, the nodes of a directed graph represent the items, and the edges represent the associations. Figure 4.1 shows 3 association rules (Bread => Milk; Bread => Butter; Eggs => Bread + Milk).

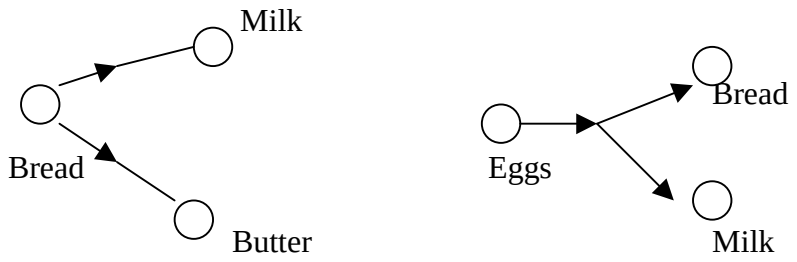


Figure 4.1 Association Rules Represented by Directed Graph

The confidence and support of the rules can be depicted using different colors and width of arrow. For example, the wider the length of arrow, the more confidence the rule has.

Directed Graph is a good visualization technique when the number of rules and the items in each rule is very small. When the number of rules and the items in each rule

become larger, it is not easy to show the rules using a Directed Graph. For example, if there are more than ten rules, an association rule graph representation is not very easy to understand because there will be lots of connections (edges) between the nodes (items). Hetzler et al. [HET1998] tried to solve this problem by animating the edges to show the associations of certain items. But the animation technique requires significant human interaction to turn on and off the item nodes.

4.1.3.2 2-D Matrix

2-D matrix is another technique to visualize the association rules. In this case, the rules are displayed in a 2-D matrix. The rule head (also called left-hand side or antecedent) items are on one axis, and the rule body (also called right-hand side or consequent) items are on the other axis. In the SGI's data mining software "MineSet" [SGI2000], 2-D matrix was used to visualize the association rules. Figure 4.2 shows one example of 2-D matrix (association rule 'Milk => Eggs'). The confidence and the support of the rule can be illustrated using the height and color of the bars.

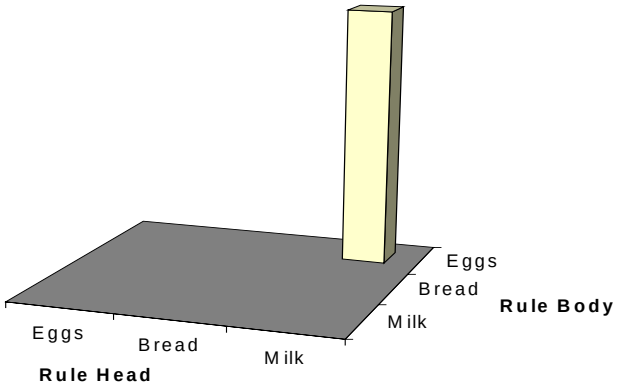


Figure 4.2 Association Rules Represented by 2-D matrix

But Figure 4.2 only can show the ‘one-to-one’ relationship, that is, only one item can be allowed in rule head and rule body, respectively. For example, in Figure 4.3, it is almost impossible to tell whether there is only one rule (Bread + Milk => Eggs) or there are two separate rules (Bread => Eggs; Milk => Eggs).

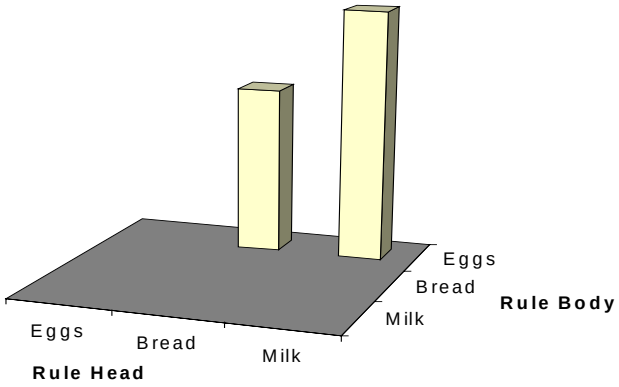


Figure 4.3 Association Rules Represented by 2-D Matrix

MineSet tried to allow multiple items in rule head and rule body by grouping the each of the items combinations in rule head or rule body as one unit. Figure 4.4 shows that rule “Bread + Milk => Eggs” can be plotted by adding one more unit “Bread + Milk” in one axis. The other rule in Figure 4.4 is “Milk => Eggs”.

Although Figure 4.4 can show ‘many-to-many’ relationship, it works well only when the items in the rule head and rule body is very few. When the number of items in the rule head is large, the number of units is expected to be very large if there are lots of combinations. This is because all combinations of items in the rule head and the rule body will be added in X or Y axes as one unit.

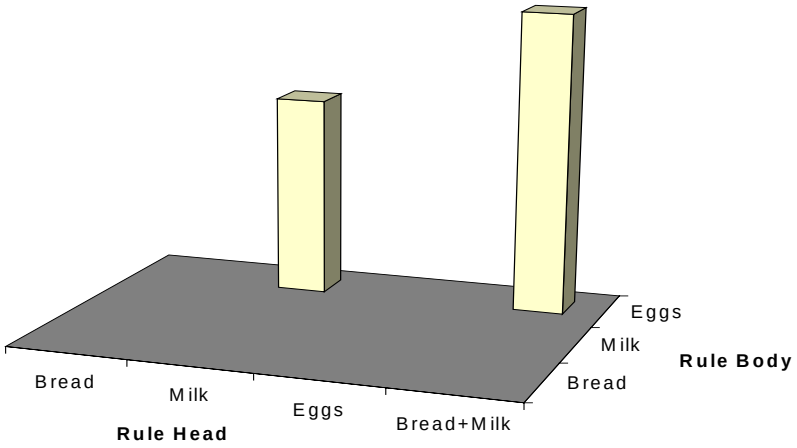


Figure 4.4 Multiple Items in Rule Head

4.1.3.3 3-D Visualization

To overcome the above problems, Wong et al. [WON1999] presented a new visualization technique using 3-D visualization.

Instead of using 'item-to-item' map in the 2-D matrix, this technique used 'rule-to-item' map. Figure 4.5 illustrates the basic idea of this technique. In Figure 4.5, the rows are items, and the columns are rules. The identities of the items are shown along the right side of matrix. The rule head and rule body can be distinguished by using two different kinds of colors. The confidence and support are displayed at the end of the matrix using the bars. The height of the bar represents the confidence of the rule. For example, Figure 4.5 shows 3 rules, they are:

- Rule 1: Bread => Milk, with confidence=90%
- Rule 2: Pumper, Bike => U-lock, with confidence=80%
- Rule 3: Bread, Butter => Milk, with confidence=85%

The are several advantages of this technique over directed graph and 2-D matrix:

1. The identity of individual items within the rule head is clearly shown.
2. The metadata such as confidence and support are shown at the end of the matrix, so the whole view is clearer to the users.
3. In theory, there is no upper limit on the number of items in the rule head.
4. It is not needed any more to create the additional units in the matrix because of the combination of the items in the rule head. The number of unites in axes is depend only on the number of items and the number of rules.

Because 3-D visualization has the above advantages, it is a big improvement over the directed graph and 2-D matrix visualization.

4.2 Rule Table

In Table 4.1, the user has to distinguish the rule head and rule body by the value of 'NULLM' and 'RULEM'. It's very difficult for the user to understand the rules. To address this problem, we can introduce the following rule table format.

Rule Head	'Imply' Symbol	Rule Body	Confidence	Support

So all the rules in Table 4.1 can be represented by this format in Table 4.2.

Table 4.2 Example of Association Rules in Rule Table Format

Bread	=>	Milk	90%	10%
Eggs	=>	Bread, Milk	85%	7%
Bike, Pumper	=>	Lock	80%	5%
Bike, Pumper	=>	Lock, Helmet	60%	3%

There are several reasons for the new rule table format:

1. In Table 4.1, the maximum item numbers in the association rules is fixed. For example, the maximum item number in Table 4.1 is 8. It can not show the rules that

have more than 8 items. If we need to display more than 8 items, the additional columns need to be added. However, the new rule table format does not have this problem.

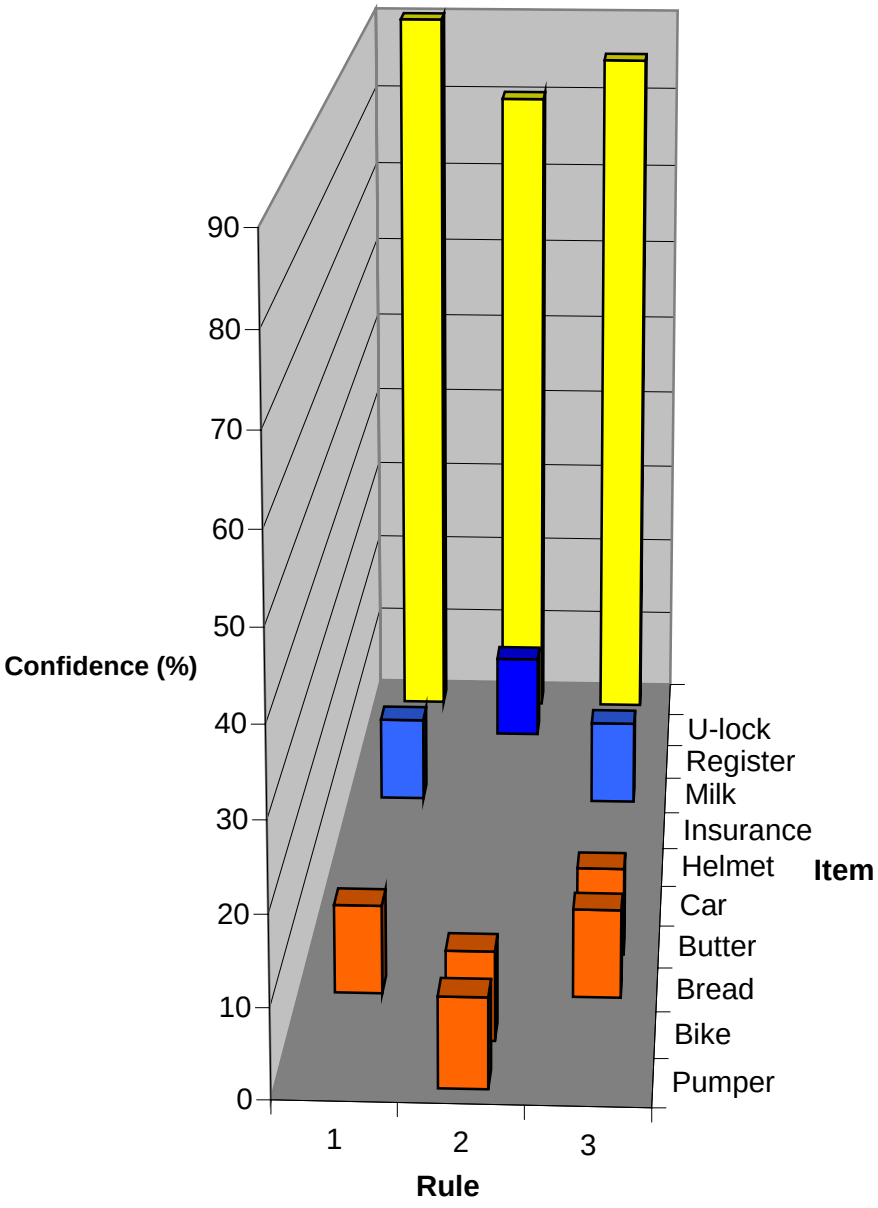


Figure 4.5 3-D Visualization of Association Rules

2. By dropping the ‘NULLM’ and ‘RULEM’ columns, the new rule table is more compact, so it takes less storage space, especially when the number of rules is very large.
3. The new rule table looks more obvious to the user since the ‘Imply Symbol’ separates the rule head and rule body, however, in Table 4.1, the user needs to figure out what the rule looks like by using ‘NULLM’ and ‘RULEM’ columns for each rule.
4. By separating the rule head and rule body, the operation of ‘Search specific rules’ will be much easier because it is not needed to use the information of column ‘NULLM’ and ‘RULEM’.

In reality, several hundreds of association rules will be generated, and it is not efficient for the user to look through all the rules generated by the rule generator. Usually the user is interested in certain rules. So the user interaction is very important. In the rule table module, the following functions should be provided to the users:

The rules can be sorted by the value of ‘Confidence’ and/or ‘Support’ so the user can find the strongest association rules.

The user can specify part or all the ‘rule head’ and/or ‘rule body’ to query specific rules that interest the users. For example, if the users are only interested in the rules that have ‘Bike’ in the rule head, the results of query should only display the rules with ‘Bike’ in the rule head, such as rules with ‘Bike’, ‘Bike, Pumper’ as rule head, etc. The rules that do not have ‘Bike’ as part of the rule head should not be seen by the user.

4.3 3-D Visualization

The 3-D visualization of Wong et al. is a big improvement over directed graph and 2-D matrix. But there still have the following problems:

1. It is best for the ‘many-to-one’ relationship. That is, the rule body has only one item. When the rule body has more than 1 item, the matrix floor is covered with many blocks.
2. The users have to distinguish the rule head and rule body by the different color of blocks. Usually not all the items in the rule head will be displayed together, so the users can not figure out what is the rule looks like at the first glance, especially when the number of items in the rule body is more than 1. Figure 4.7 shows this problem. In Figure 4.7, Rule 4 means rule ‘b, e, i, j => d, g’ with confidence=58%. But because not all the items in the rule head display at the one end, and not all the items in the rule body display at the other end, it is not clear to the user of how the rule looks like. It is idea if all the items in the rule head can be put on the one end, and all the items in the rule body can by put on the other end so the user can see the rules very clearly.
3. Although it can show lots of rules at the same time, the interaction between the visualization system and the user is definitely needed because most of the time, the users are only interested in some specific rules with some specific items in the rule head and/or rule body. So the system should provide the user a very good interface to interact with the system.

To address the above three problems, the new 3-D visualization system should try to achieve the following goals:

1. It should have a very good interactive graphic user interface. The user can sort, filter the rules according to the user’s interest.
2. The items in the rule head and the items in the rule body should be separated very obviously. That means, it is the best if all the items in the rule head are at the one end,

and all the items in the rule body are at the other end. If this goal can be achieved, the user can understand the rules at the first glance.

3. Since items of the rules are presented with blocks in the chart, the fewer blocks exist in the chart, the clearer view the user can get.

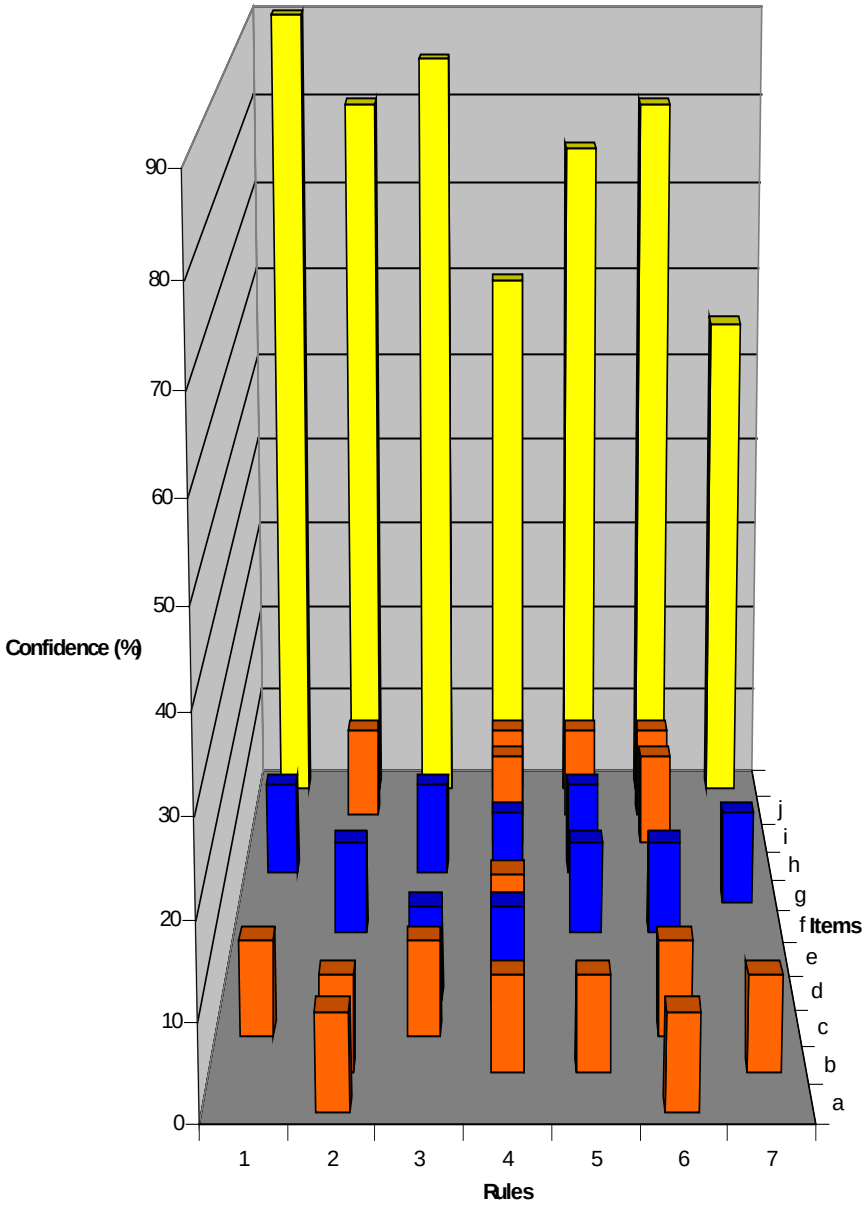


Figure 4.7 Association Rules that have more than 1 Item in Rule Body

Based on the above goals, we improved the 3-D visualization technique of Wong et al. by adding the following new features:

1. There will be a graphic user interface provided to the user to do the sorting, filtering, animation, etc. It will be very flexible for the user to use. Goal #1 is achieved. Details of the user interface will be discussed in Chapter 6.
2. The items in the rule body are shown in axis X using the text. So the rule head and rule body is visually separated and the user can see what the rules look like at the first glance. Goal #2 is achieved.
3. Removes the blocks of items in rule body, as a result, on the chart only the items in the rule head remains, and only one color is enough, and there are fewer blocks on the chart. Goal #3 is achieved.

Figure 4.8 illustrates the basic idea of the above modification.

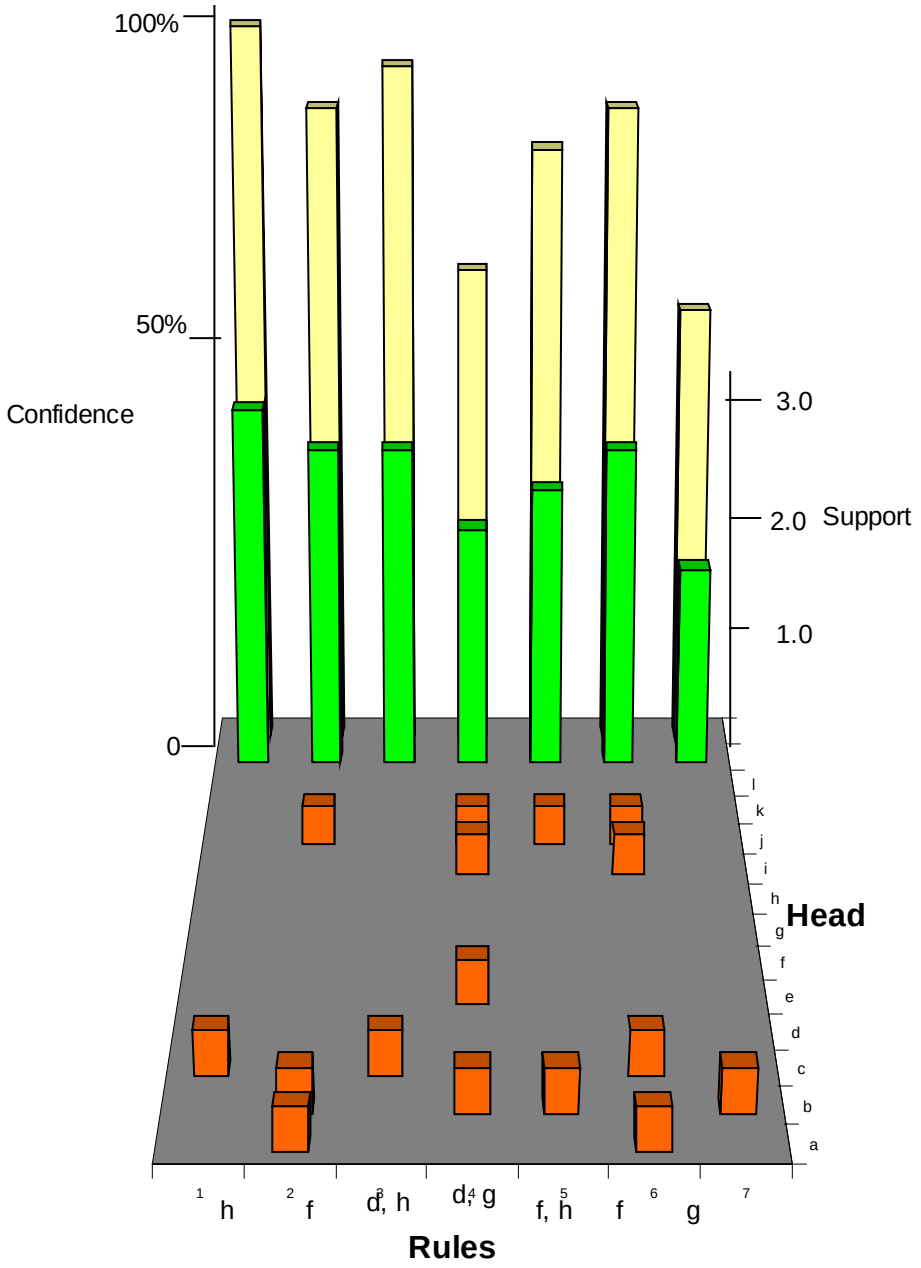


Figure 4.8 Association Rule Visualization

CHAPTER 5
SYSTEM IMPLEMENTATION

In the previous chapters, we presented the several different association rule algorithms, and then provided our design of association rule visualization technique. The input of the rule generation algorithm is a table with two columns “tid, item”, and the output is a table with each rule occupies one row. However, in reality, the data are usually not exactly in the form of “tid, item”, and some of them are in text format, instead of integer format. For example, in the supermarket, each transaction consists of transaction id, and items that each customer buys. In this case, the date and time may work as the transaction id, and the items can be identified by their names. To fit this kind of data set into the input format of our rule generation algorithm, we should have a very good graphic user interface (GUI) for the user to manipulate their existing data set to feed to our rule generation algorithm. We choose Java as the programming language for this project based on the following reasons:

1. Java program is platform independent. Instead of generating the executable machine instructions by the C++ compiler, Java compiler outputs Java byte codes. Java byte codes are instructions written for some virtual Java machines that do not really exist. These byte codes run through the Java Virtual Machine (JVM), which works as an interpreter to execute the Java byte codes. There is a different JVM emulator for each different type of machines, so Java

program can be compiled only once and the compiled class file can be run on any machine that has JVM.

2. Because in reality, the user may have data stored in several different database management systems, it is very useful for the mining algorithm to be able to retrieve the data from different database management systems. Java provides the Java Database Connectivity (JDBC) to have this ability. Especially for the pure SQL92 approaches, the Java program for DB2 is almost the same as for Oracle, except some features the each individual DBMS have.

For the output of generated rules, we also need a good GUI to let the user get the information that interests the user very easily. There are two ways to implement the rule visualization system. The first one is to use the existing graphics software tools to display the association rules. There are some softwares such as SAS, ArcView that can be used to display the designed 3-D graph. By using this choice, it takes less time to implement but there is not much flexibility, especially for the graphic user interface part. You can not get the GUI as you designed. The second way is to implement from scratch using Java. There are some advantages to use Java compared to using existing software:

1. Because the system will be built from the scratch, we can have whole control of how it works, and it will give us the flexibility to control the GUI and make it exactly the same as what we designed.
2. The system can be integrated into the association rule generator and optimizer that we have implemented, so it will become an integrated and complete system.

3. By using Java, it will not only run as the application, also it can be put on the web and run as the applet.
4. Java provides a set of Java 3D APIs that serve as the interface to a sophisticated three-dimensional graphics rendering system. A Java 3D program creates instances of Java 3D objects and places them into a scene graph data structure. Despite all of the 3D functionality, the Java 3D API is still straightforward to use.

Because of the above reasons, we choose Java 3D to implement the association rule visualization module.

In this chapter, the system architecture of our software is presented in Section 5.1. The interfaces of rule generator and rule visualization, as well as their implementations are detailed in Section 5.2 and 5.3.

5.1 System Architecture

Our system is based on the two-tier model because no business logic is incorporated in our system. The system architecture is shown in Figure 5.1.

In Figure 5.1, the database resides in the server machine. The stored procedures (Oracle) and UDFs (DB2) also reside in the server side. Our Java application runs in the client machine. It consists of several modules: LogIn, Rule Generator, and Visualization module. LogIn module is used to connect to the database server. Rule Generator is used to mining the association rules given the information provided by the user. Visualization module consists of two sub-modules Rule table and 3-D visualization. These modules can be accessed using the Main window. The interfaces and their implementation are presented in the following sections.

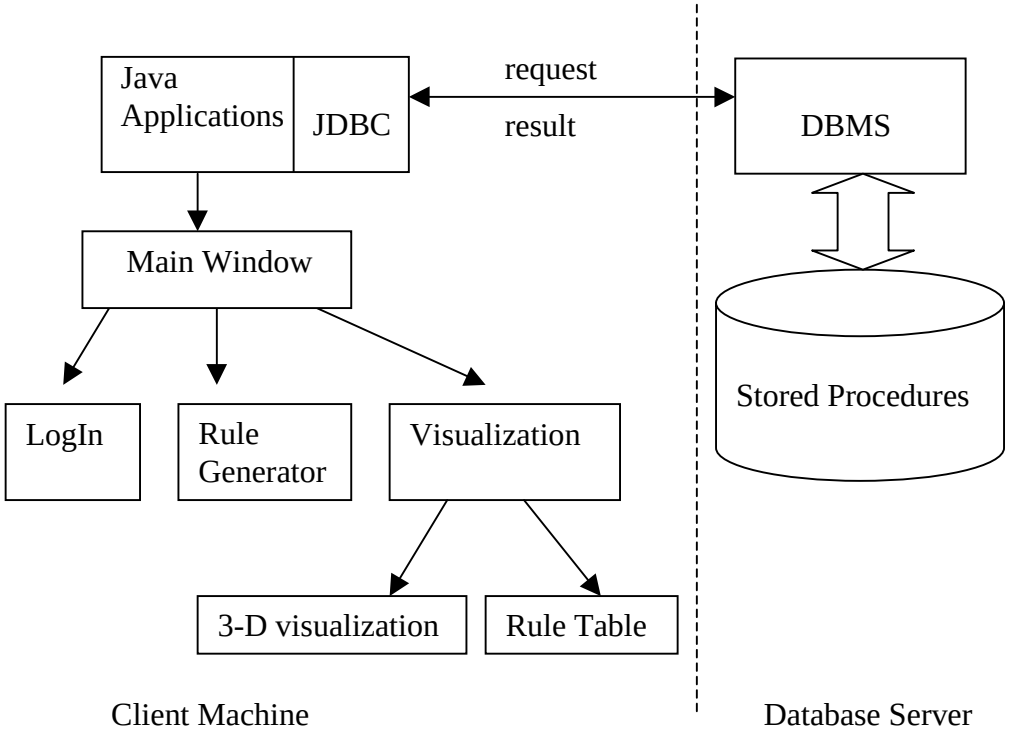


Figure 5.1 System Architecture

5.2 Main Window

Figure 5.2 shows the main window of our association rule software. The main window consists of the menu, toolbar, and a text area. The operations of rule generation and rule visualization are mainly done through the menu. Under the “File” menu, there are several submenus, such as “Connect”, “Disconnect”, “Save to File”, “Clear Messages”, “Exit”. The submenu “Connect” is used to let the user connect to a specified DBMS, such as Oracle, or DB2 since this software is designed to be able to retrieve the data from different Database Management Systems. “Disconnect” submenu is to simply let the user disconnect from the DBMS after he finished the mining operations. But if the

user forgot to disconnect from the DBMS, when the application is terminated, the connection will be disconnected automatically. “Save to File” and “Clear Messages” submenus are related to the log messages generated by the mining operations. For each association rule generation algorithm and each input data set, there will be the some messages output to let the user know what had happened. After each operation, the user can choose to save these messages into a text file or clear these messages from the window. For each major function, such as “Connect”, “Disconnect”, “Rule Generation”, “Exit”, there is an icon on the toolbar corresponding to the operation for the user’s convenience. So the user can just click the icon on the toolbar once instead of using the menu.

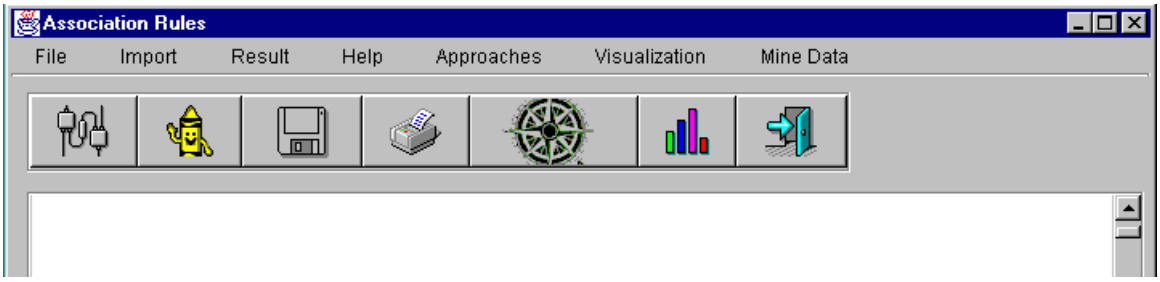


Figure 5.2 Main Window of Association Rule Software

We use JBuilder 3 as the software development tool to implement our project. JBuilder provides an Integrated Development Environment (IDE), which makes interface design, program debugging very efficiently. The menu can be implemented using the Menu Designer. All the objects in the main window can be designed visually.

5.3 LogIn Module

After the user chooses “Connect” menu item, a Login window will be brought up. The appearance of login window is shown in Figure 5.3. In this login window, the user

needs to give the information of user id, password, the DBMS, and the database name that related the specified DBMS. The password is masked using "*" for the security reason, and the DBMS names have been predefined, so the user just selects from the provided Database Management Systems. The database name has not been predefined and the user has to fill the information himself because the software has no idea of what databases have in a particular DBMS until the connection has been established, and in order to establish a connection, a database name has to be provided. In the login window, there also exists a checkbox called "Admin". This checkbox is used to let the user decide if he wants to choose a particular miming algorithm. If the "Admin" checkbox is not checked, the "Approach" submenu will be disabled so that the user only needs to give the input data set, and the software will decide to choose the best algorithm from the available 6 approaches for the given data set. If the "Admin" is checked, the user has the freedom to choose any available approaches to generate the association rules. If the user has time, he can save the output rules from different approaches and compare to each other for the correctness.

After the user provided all the needed information, the user can choose to "Connect" to the DBMS, or in case he makes some mistakes, he can choose to clear the information and fill it again.

The LogIn module is implemented with "LogIn.class". Connection to the server is made possible through JDBC. The main method of the LogIn class is "btnConnect_actionPerformed", which is associated with the button "Connect" in the LogIn window. This method is shown in Figure 5.4.

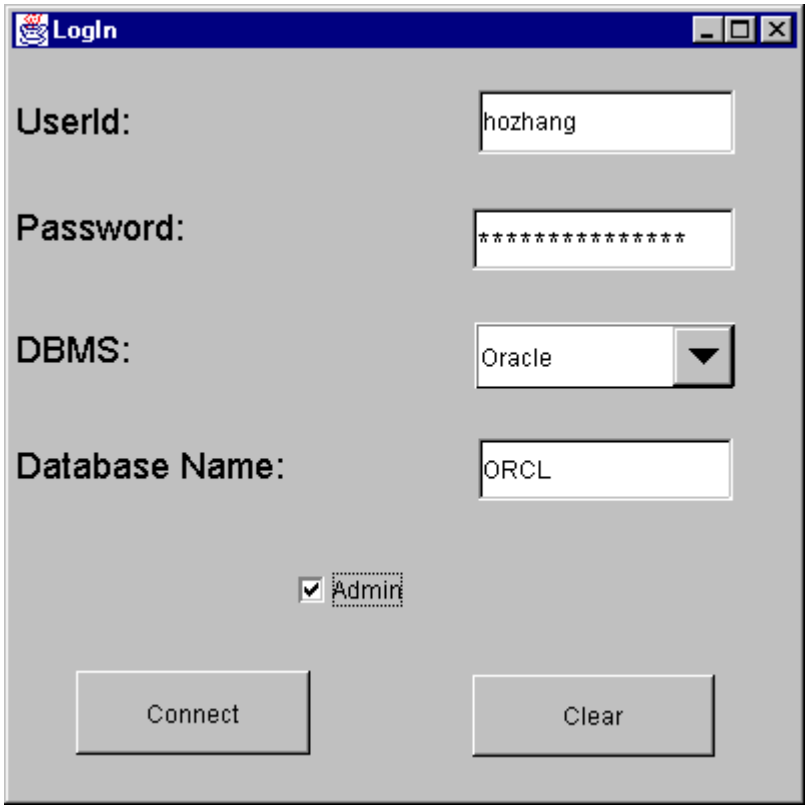


Figure 5.3 Login Window of Association Rule Software

There is a file named “Mining.config” to store the different DBMS server’s information, such as host IP address and port number. Each DBMS has one entry in this configure file. For example, the entry of Oracle is “[ORACLE] 128.227.176.49:1521”, which indicates Oracle resides in the host machine with IP address 128.227.176.49 and the port number is 1521. In case Oracle is moved to another machine, the use only needs to modify the host IP address in this file. So the program does not need to be changed.

Method “btnConnect_actionPerformed” first gets the DBMS information from the LogIn window, then it is compared with the entries of file “Ming.config”. If there is a match, the host IP address and port number is retrieved from that entry. The other information needed to log in to the DBMS, such as user name, password, database name

can be obtained through the user's input in the LogIn window. Once all the information is ready, JDBC first loads the corresponding database driver using the method "Class.forName". After the driver is loaded, a connection can be made using the method "DriverManager.getConnection (url, user, passwd)". The highlighted lines of code in Figure 5.4 illustrates how to load the database driver and how to make a connection to the server.

```
void btnConnect_actionPerformed(ActionEvent e)
  {
       fin = new FileInputStream("Mining.config");
       while((bytes_read = fin.read(buffer)) != -1);
       fileText = new String(buffer);
       Vector vc=new Vector();
       StringTokenizer st = new StringTokenizer(fileText);
       while (st.hasMoreTokens())
            vc.addElement(st.nextToken());
       for(int i=0;i<vc.size();i++)
       {
         if(vc.elementAt(i).toString().equals("[ORACLE]"))
             server = vc.elementAt(i+1).toString();
       }
       if ( (cmbDBMS.getSelectedItem().toString()).equals("DB2") )
       {
          Class.forName("COM.ibm.db2.jdbc.app.DB2Driver");     //for .app
          url = "jdbc:db2:";
          url = url.concat(db);
       }
       else if ( (cmbDBMS.getSelectedItem().toString()).equals("Oracle") )
       {
          Class.forName("oracle.jdbc.driver.OracleDriver");
//        url = "jdbc:oracle:thin:@tokyo.dbcenter.cise.ufl.edu:1521"
//          server = "128.227.176.49";
          url = "jdbc:oracle:thin:@" + server + ":";
          url = url.concat(db);
       }
       con = DriverManager.getConnection (url, user, passwd);
}   // end of btnConnect_actionPerformed
```

Figure 5.4 btnConnect_actionPerformed Method

5.4 Rule Generator

For each input data set, some parameters have to be specified by the user for the association rule generation. This kind of information can be input by the Parameter Input window. Parameter Input window is shown in Figure 5.5. For the data source, because the data is not always in the same table, and sometimes it is needed to obtain the data from two or more different tables, the user should have the ability to select multiple tables as the data source. For this reason, the available table names have been populated in the list box. The user can choose multiple tables by using “Shift” or “Control” key. For the multiple tables, the “Join” and “Union” operations are also provided to let the user manipulate the data source from multiple tables and combine them into one table. The user may also want to specify the lowest support and confidence value to get the interested association rules. The value of stop level is used to let the user decide that after how much passes that the user wants the rule generation needs to be canceled. The “Statistics” button is used to show the user some basic statistics (such as number of transactions, number of rows, number of different items, average number of items in each transaction, etc) of the selected tables. After all of the information is completed, the user can click the “Generate Rules” to begin to merge the data from different tables. Then the association rule generation algorithm will be called to generate the rules.

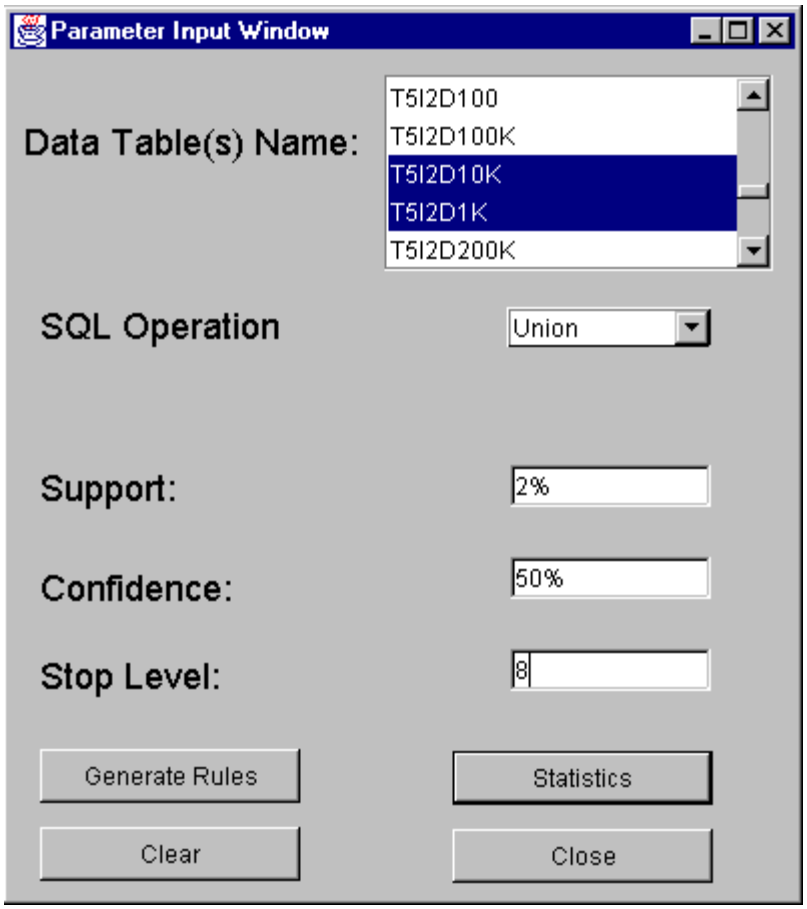


Figure 5.5 Parameter Input Window of Association Rule Software

The class that related to Parameter Input window is “ParameterInput.class”. The key method of this class is to retrieve all the available table names from the given database and show them to the user. Figure 5.6 shows the implementation of this task. We used two different mechanisms for DB2 and Oracle. In DB2, we utilized the metadata of the database. The method “getTables” in the “DatabaseMetaData” class can be used to return all the table names in the database. In Oracle, we used the data dictionary. All the table names are stored in the system table “user_tables”. We can obtain all the table names using a simple query.

```
Statement stmt = LogIn.con.createStatement( );
DatabaseMetaData dbmd = LogIn.con.getMetaData();
 if(LogIn.cmbDBMS.getSelectedItem().toString().equals("DB2"))
{
            String[] type={"TABLE"};
            ResultSet rs =dbmd.getTables("",LogIn.user_id.toUpperCase(),"",type);
            ResultSetMetaData rsmd = rs.getMetaData();

             boolean more = rs.next();
             while ( more )
            {
                String rsts=rs.getString(3);
                tables.addElement(rsts);
               more = rs.next();   // move to next row
            }
           rs.close();
}               // end of first 'if'
else if(LogIn.cmbDBMS.getSelectedItem().toString().equals("Oracle"))
{
          String qs="select table_name from user_tables";
          ResultSet rs=stmt.executeQuery( qs );
          boolean more = rs.next();
          while ( more )
          {
             String rsts=rs.getString(1);
             tables.addElement(rsts);
            more = rs.next();   // move to next row
          }
         rs.close();
}                 // end of 'if'
stmt.close();
```

Figure 5.6 Retrieve All the Table Names Available in the Database

5.5 Visualization Module

In the association rule software, we implemented two kinds of rule visualization tools to view the mining results: rule table and 3-D graphic. Each tool allows the user to work in the interactive environment. This section describes these tools in detail.

5.5.1 Rule Table

Figure 5.7 shows the rule table visualization window. In this window, all the rules shows according to the rule format introduced in Chapter 4. Because usually hundreds of

rules will be generated, it is not easy for the user to view all of the rules at one time. In addition, the user may only interest in some certain rules. For example, in order to answer the question “what are the items that related to item Lock?”, he may only need to view the rules that have item “Lock” contained in the rule head and rule body. All the rules that do not have “Lock” in the rule do not interest the user. Rule table visualization window provides this function. In this window, the user can specify any kinds of query criteria. For example, if the user wants view the rules with the item “Lock” in the rule head, and he also wants the minimum confidence of the rules is 50%, he can construct this query by clicking the corresponding list box and radio button in the window. The filtered rules can be obtained by clicking the “Show Rules” button.

The related class of Rule Table is “Rule_Table.class”. The constructor of this class reads all the records from the table RULES and all the tuples are presented to the user. This is done using the simple query “Select * from RULES”. The key method of this class is that associated with button “Show Rules”. The implementation of this method is illustrated in Figure 5.8.

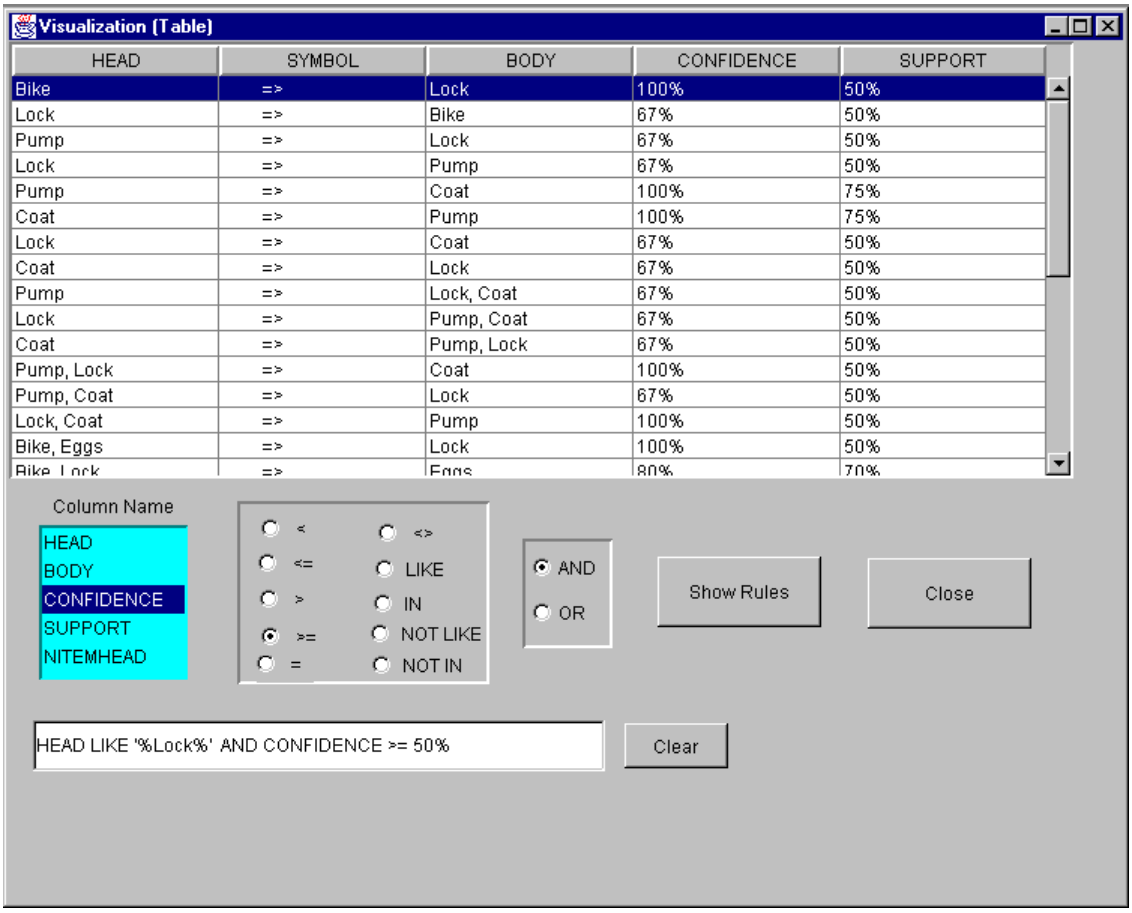


Figure 5.7 Rule Table Visualization Window with Filter Function

```
void btShowRules_actionPerformed(ActionEvent e)
 {
  // construct the where clause of the sql query, such as "where head like '%Milk%' and support>3%"
  String wherestring = " where " + txtWhere.getText();

  // because the user will input query like 'SUPPORT > 50%', we need to
  // remove % in this case
      …
        …
 // end of remove extra '%' following 'CONFIDENCE' AND 'SUPPORT'

  // lanuch the filtered table of rules, pass the table name, and the where clause
  Rules_Table_Filter RulesFilterdlg = new Rules_Table_Filter(this, Rules_tableName, newWhereString);
    // launch the Rule_Table_Filter window
     …
 }
```

Figure 5.8 Show_Rule Method

In Figure 5.8, the key point is to construct the *where* clause for the query. We provide the user a set of standard SQL operators, such as ‘LIKE’, ‘NOT LIKE’, ‘IN’, ‘NOT IN’, ‘>’, ‘>=’, ‘AND’, ‘OR’, etc. For example, the query “Head Like ‘%Lock%’” means that any rules that have “Lock” in the rule head satisfies the requirement. After the user finished clicking the operators, the *where* clause is shown in a text box. The string in the text box needs to be further processed (remove % from the support value, etc) for the string becomes a *where* clause that any DBMS will accept it. At last, the final *where* clause, together with the “RULE” table name, is passed to another class Rule_Filter_Table to show the user filtered rules.

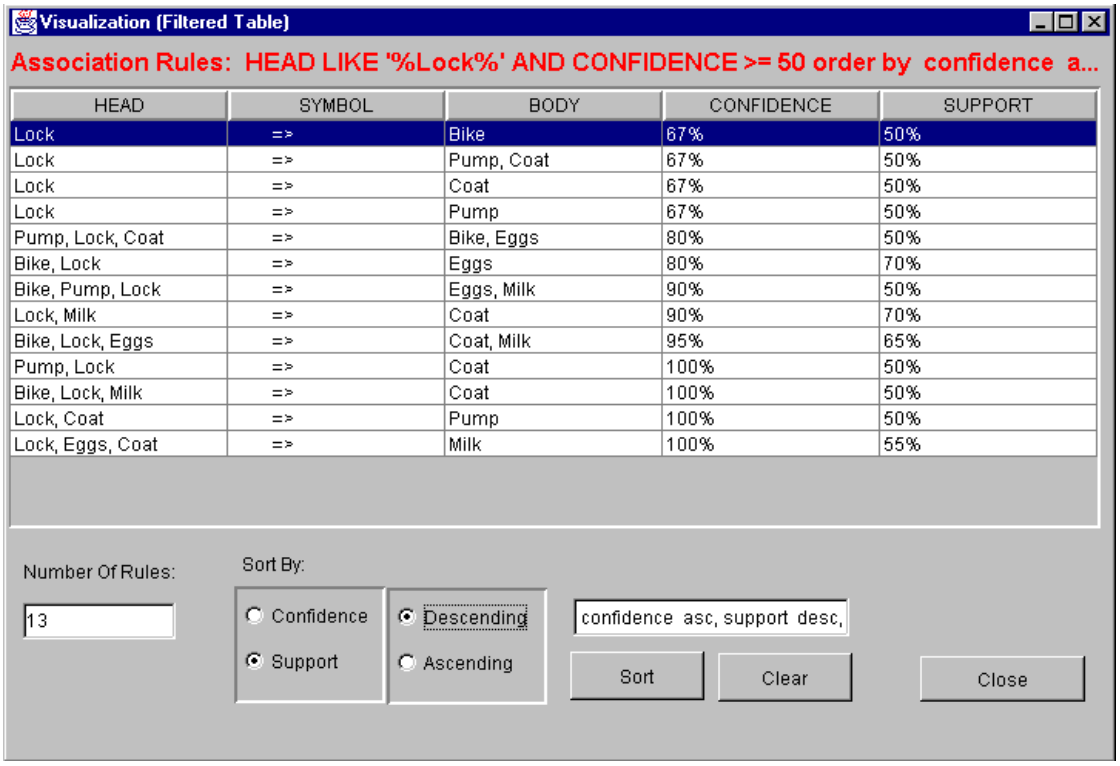


Figure 5.9 Rule Table Visualization Window with Sort Function

After filtering the rules, the user can also sort these rules by “confidence”, and “support” columns with descending or ascending order. Figure 5.9 shows one example of filtered rules with the query “HEAD LIKE ‘%Lock%’ AND CONFIDENCE >= 50%” with the order of “confidence ascending, support descending”. This window also shows the number of rules that satisfy the above query.

One issue about rule table is the feature of DBMS independence. The rule table works on a table representation. Because all the operators provided to the user are standard SQL operators, the corresponding SQL query can be executed in any DBMS. So by using JDBC, the code for retrieving the rules from any DBMS is exactly the same and no other extra codes are necessary for the different DBMSs.

5.5.2 3-D Visualization

Besides the rule table visualization tool, the other visualization tool is 3-D graphic. First the rules are classified according to the number of items in the rule head. Figure 5.10 shows the different categories of rules based on the number of the items in the rule head. In Figure 5.10, it shows that there are three categories of rules, which have 1, 2, and 3 items in the rule head. In each category, the number of rules that falls into each confidence or support interval (50%-60%, etc) is labeled. The labels for confidence and support are in different colors. In Figure 5.10, it shows that for all the rules which have 1 item in the rule head, 8 rules have the confidence between 60% to 70%, and 2 rules have the confidence between 90%-100%. As to the support, 9 rules have the value of 40% to 50%, and only 1 rule has the value of 70%-80%. Double click the column bar will invoke the 3-D visualization window that shows the rules with the particular number of items in the rule head.

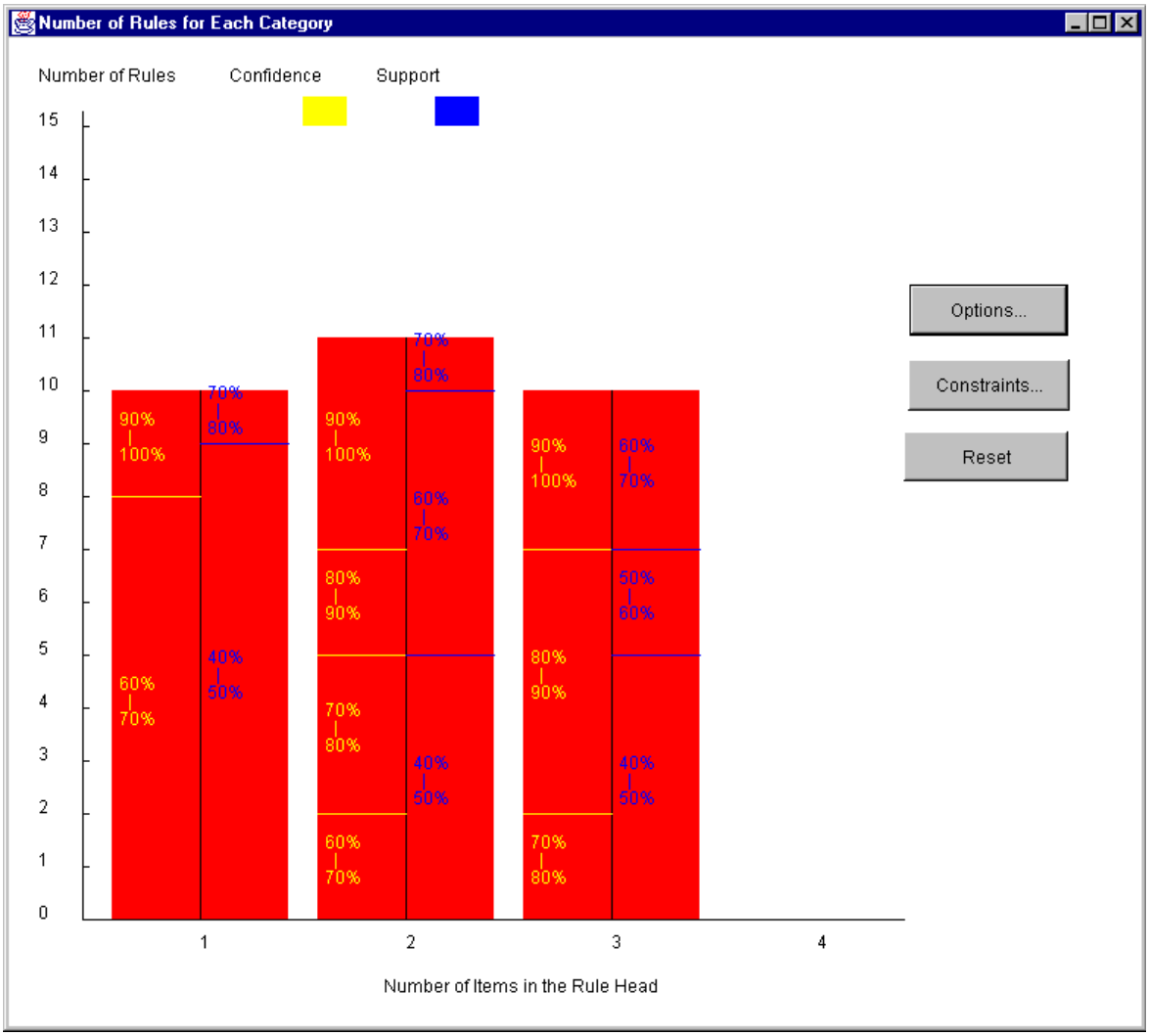


Figure 5.10 Different Categories of Rules Based on # of Items in the Rule Head

The implementation of the window “Number of Rules for Each Category” is class “TwoD_NumberOfRules.class”. The constructor retrieves all the rules from table RULES and classified them based on number of items in the rule head, support, and confidence. The results are shown to the users with the format of column bar.

The user can customize the above window dynamically according to the number of items in the rule head and the number of the rules. The default values of these two are

8 and 15, respectively. If the number of items in the rules is fewer than 8, the user can lower this value so that each column can have more space. These changes can be made by the options window, which is shown in Figure 5.11. In this figure, the number of items in the rule is represented by “Max Scale of X-axis”, and the number of rules is represented by “Max Scale of Y-axis”.

The implementation of the “Options” window is class “TwoD_Options.class”. It modified the attributes of class “TwoD_NumberOfRules.class”. When that window resizes, the “paint” method will be called again and the window will be refreshed with the modified attributes.

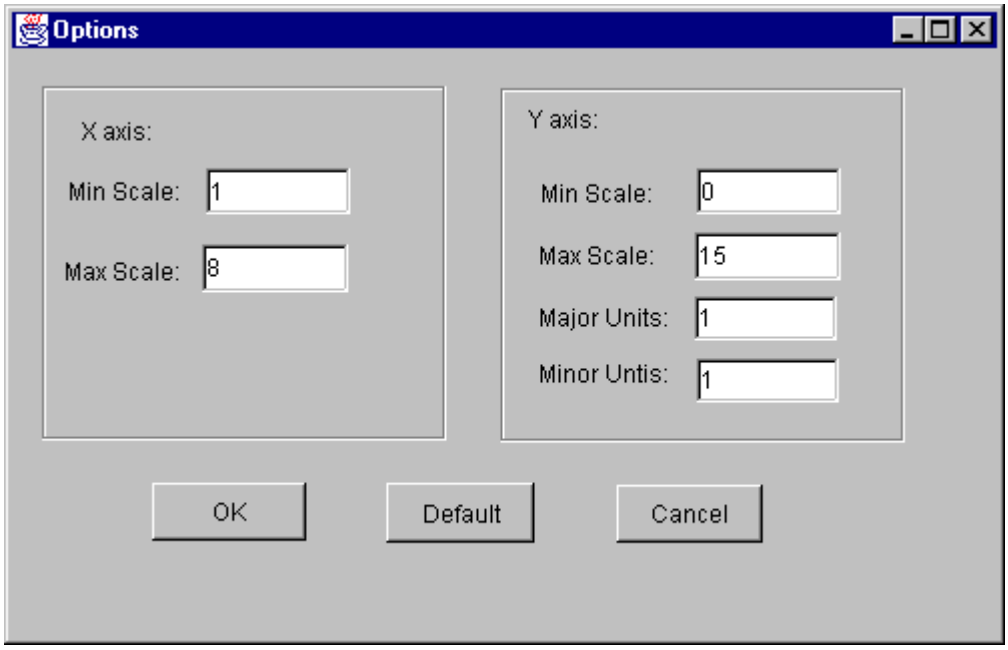


Figure 5.11 Options Window in Association Rule Software

For each category of the rules, just like in rule table visualization tool, the user can also specify the constraint to filter the rules. The operations in Figure 5.12 are almost the same as those in rule table visualization tool. The only difference is that Figure 5.12

provides the filtering and sorting function in one window. The implementation of this interface is class “Add_Constraints.class”. The implementation is similar to the class “Rule_Table.class”, which constructs the *where* clause to retrieve the rules with certain conditions.

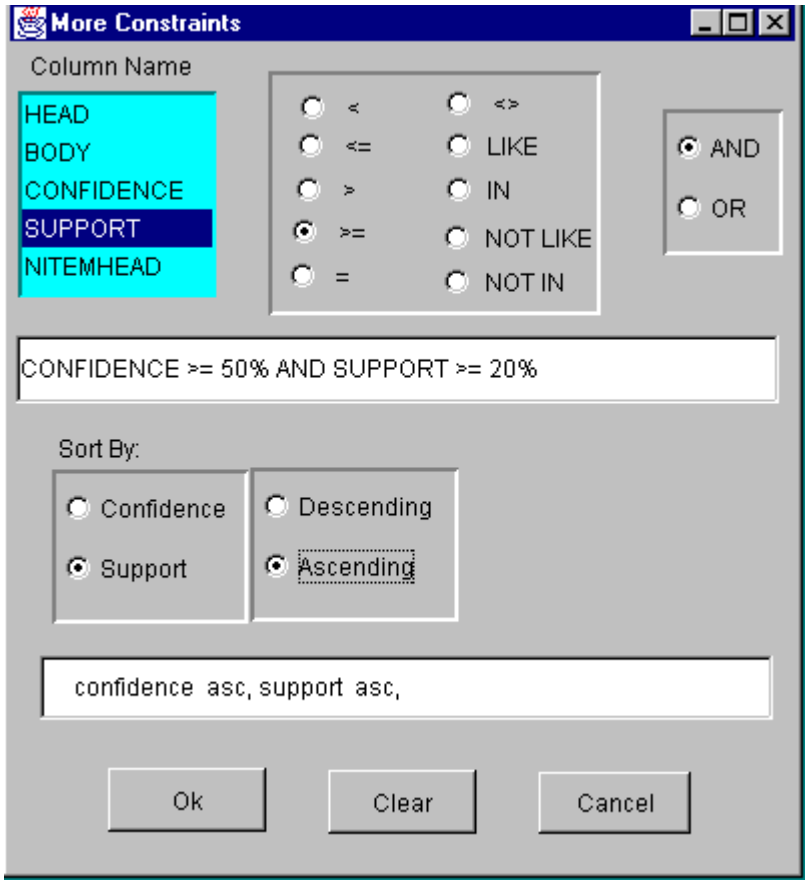


Figure 5.12 Constraints Window in Association Rule Software

Figure 5.13 is invoked by double clicking one of the column bars in Figure 5.10. For example, if the user double click the column bar that labeled wit the “Number of items in rule head = 3”, it brings up Figure 5.13. In Figure 5.13, each row represents one item, and each column represents one rule. The names of the items are labeled along the right side of each row. Each item in the rule head has a small block covered on the floor.

The names of the items that are in the rule body are labeled along the X-axis. The confidence and support for each rule are marked at the far end of the floor with different colors. For example, Figure 5.13 shows 10 rules. The first rule is “Coat, Lock, Pump => Bike, Eggs with confidence of 80% and support of 50%.” From Figure 5.13, we can also easily figure out which item appears in the rule head mostly. Here item “Bike” appears in 6 out of 10 rules as part of the rule head.

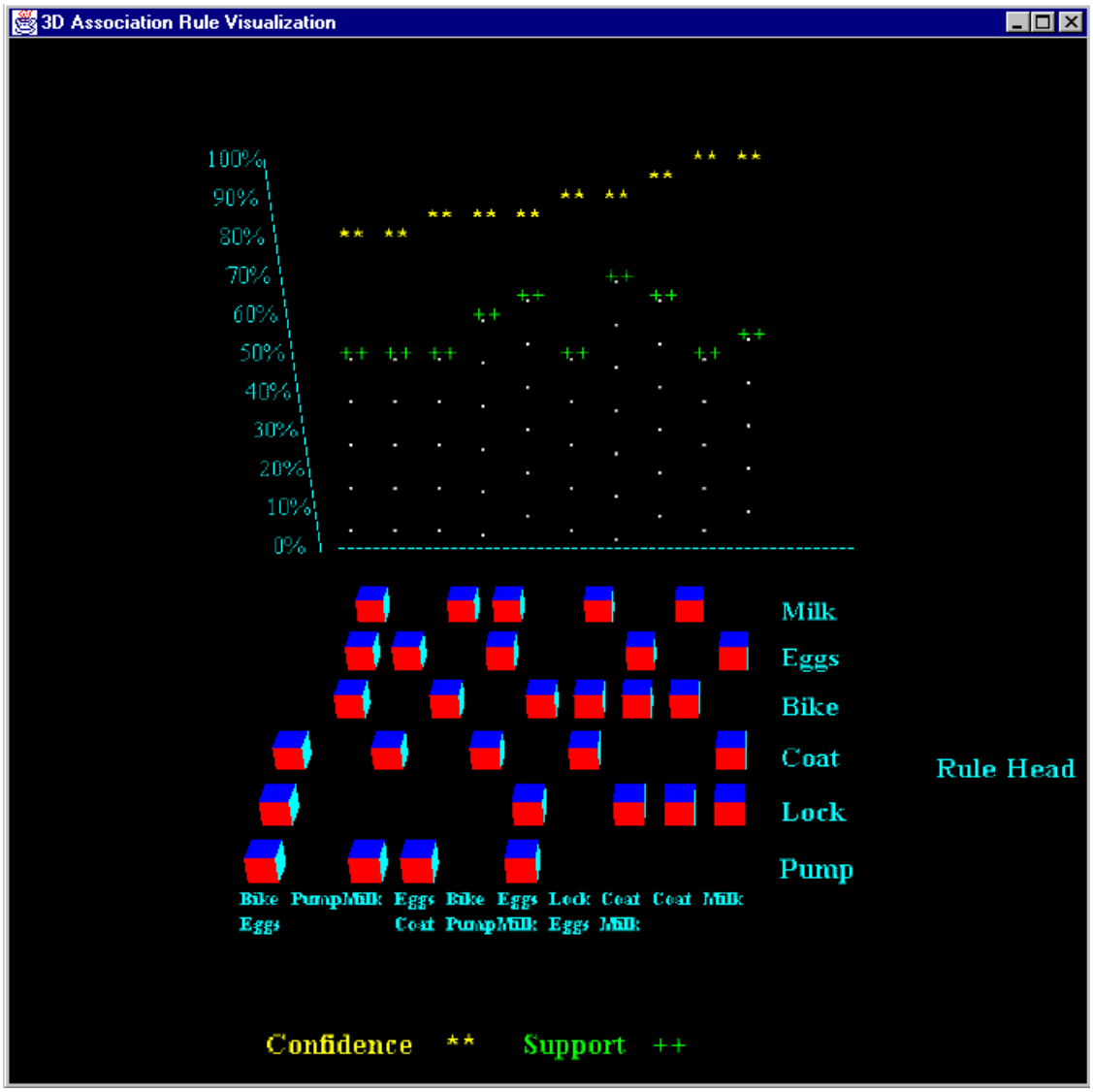


Figure 5.13 3-D Visualization Window in Association Rule Software

We used Java 3D, which is a standard extension to the JDK 2, to develop our visualization tool. The Java 3D API is a hierarchy of Java classes which serve as the interface to a sophisticated three-dimensional graphics rendering and sound rendering system [SUN1999]. A Java 3D program creates instances of Java 3D objects and places them into a scene graph data structure. Basically there are five steps to create a Java 3D program, as illustrated in Figure 5.14 [SUN1999].

1. Create a Canvas3D Object
2. Create a SimpleUniverse object which references the earlier Canvas3D object
    a. Customize the SimpleUniverse object
3. Construct content branch
4. Compile content branch graph
5. Insert content branch graph into the Locale of the SimpleUniverse

Figure 5.14 Simple Recipe for Writing Java 3D Programs using SimpleUniverse.

As shown in Figure 5.14, in order to develop a Java 3D program, we first need to create a Canvas3D object to serve as the canvas of the 3D objects. The second step uses a *SimpleUniverse* class to reduce the time and effort needed to create the view branch graph. The *SimpleUninverse* class hides lots of the details of Java 3D programming. As a result, the programmer has more time to concentrate on the content. The key point in Java 3D programming is step 3, where the programmer develop his own 3D objects and contents. Once all the objects are ready, step 4 and 5 just compile the content branches and add them to the *SimpleUniverse* class. Because this class is associated with the Canvas3D object we created earlier, the content branches we developed will be displayed on the screen.

The implementation of our 3-D visualization is in class “ThreeD_General.class”. Figures 5.15 and 5.16 are from our implementation and they illustrate the above five steps using *SimpleUniverse* class. Next we walk through the code in these figures.

```
// main method to implement the 3D rule visualization
  public void paint(Graphics g)
  {
     Canvas3D canvas3D = new Canvas3D(null);                    --- Step 1
     this.getContentPane().add("Center", canvas3D);

    // SimpleUniverse is a Convenience Utility class
     SimpleUniverse simpleU = new SimpleUniverse(canvas3D);     --- Step 2

     BranchGroup scene = createSceneGraph();                    --- Step 3 & 4
                    …
                    …
   // This will move the ViewPlatform back a bit so the objects in the scene can be viewed.
     simpleU.getViewingPlatform().setNominalViewingTransform();

     // add all the sub branch groups into the map.
     simpleU.addBranchGraph(scene);                             --- Step 5
…
…
}   // end of 'paint'
```

Figure 5.15 Paint Method in ThreeD_General Class

As shown in Figure 5.15, a Canvas3D object *canvas3D* is created in the first step. In the second step, a SimpleUniverser object *simpleU* is created which references the earlier created Canvas3D object *canvas3D*. As to step 3, we classified all the objects into several categories and designed one function for each of these categories. These categories include:

- Items in rule head of all the rules
- X-axis
- X-axis label
- Y-axis
- Y-axis label
- Support
- Confidence

- Support label
- Confidence label
- Items name.

The purpose of classify these categories is for the convenience of update our visualization system. For example, if we want to change the color of support, we only need to modify one function that is related to this category. These functions are developed to create the objects we needed.

Figure 5.16 illustrates one of these functions *createSceneGraph*. This function is used to create all the items in rule head of each rule. Each item is represented with a small cube and all the cubes are displayed on a three-dimensional graph. The default of the cube shows only one face. To show more than one face of the cube, we need to rotate the cube. Rotation can be made about X-axis, Y-axis or Z-axis. The method *rotX*, *rotY* and *rotZ* in class *Transform3D* are used to for this task. In order to rotate about two axes, two different transformations should be specified for a single visual object. Figure 5.16 shows how to combine the two transformations to make a complex rotation.

After we specified the rotation, we began to retrieve the data from RULE table. All the items in rule head of each rule are retrieved and stored in a *Vector*. Then a cube is created for each item retrieved using the class *ColorCube*. The position of each cube in the three-dimensional graph is set by the *setTranslation* method in *Transform3D* class. The parameter of method *setTranslation* is a *Vector3f* object, which stores the position of each cube in three-dimensional graph.

After all the cubes have been created, we compile these objects in the content branch in step 4. Compiling the content branch converts it to a more efficient form, thus this step is used for the optimization.

```
public BranchGroup createSceneGraph()      // create the items
  {
    // Create the root of the branch graph
   BranchGroup objRoot = new BranchGroup();
   Appearance app = new Appearance();

   TransformGroup objRotate = null;
   Transform3D transform = new Transform3D();
   Transform3D transformZ = new Transform3D();
   transform.rotX(Math.PI/6.0d);
   transformZ.rotZ(Math.PI/2.0d);   // rotate to adjust the viewer's color
   transform.mul(transformZ);

   for(int i=0;i<rcount;i++)

   {
     Vector vCurHead = new Vector();
     String TotalHead = vHead.elementAt(i).toString().trim();
     StringTokenizer st = new StringTokenizer(TotalHead, ",");
     while (st.hasMoreTokens())                    // add all items in the current rule head
        vCurHead.addElement(st.nextToken().trim());    // into the vCurHead

     for(int j=0;j<vCurHead.size();j++)
     {
       int jPos=0;
       String CurHead = vCurHead.elementAt(j).toString().trim();
       for(int w=0;w<vDisctHead.size();w++)
       {
         if(CurHead.equals(vDisctHead.elementAt(w).toString().trim()))
         {
              jPos = w;
              break;
         }
       }     // end of 'for(w)'
       // create ColorCube objects
       transform.setTranslation(new Vector3f( (float)(-1.0+i*0.1), (float)(-0.6+jPos*0.1), (float)(-1.2-
jPos*0.1)));
       objRotate = new TransformGroup(transform);
       objRotate.setCapability(TransformGroup.ALLOW_TRANSFORM_WRITE);
       objRotate.setCapability(TransformGroup.ALLOW_TRANSFORM_READ);
       objRoot.addChild(objRotate);
       objRotate.addChild(new ColorCube(0.03));
     }   // end of inner 'for'
   }    // end of outer 'for'
           // Let Java 3D perform optimizations on this scene graph.
   objRoot.compile();                                                    --- Step 4
            return objRoot;
  }  // end of CreateSceneGraph method
```

Figure 5.16 Content Branch for Items in the Rule Head of All Rules

As in rule table module, in the 3-D visualization module, all the operators that we used for database access, such as ‘LIKE’, ‘IN’, ‘NOT’, ‘AND’, ‘OR’, ‘>’, etc, are standard operators. As a consequence, using JDBC, all the operations in our visualization tool are identical for any DBMS. No extra code is necessary for different DBMSs. So our visualization tool is purely independent of specific DBMS.

CHAPTER 6
CONCLUSION AND FUTURE WORK

6.1 Conclusion

We first discussed the architectures of JDBC application. Between 2-tier and 3-tier architectures, 2-tier is chosen because no business logic is incorporated and hence addition of a tier adds complexity without any gains for what we are trying to do. Next, the advantages and disadvantages of two data mining architecture alternatives "Cache-Mine" and "SQL-based" are analyzed.

We used association rule mining to compare these two architecture alternatives. Intelligent Miner is chosen as the representative of "Cache-Mine" architecture. We implemented three mining algorithms (K-Way Join, 2-Groupby, and Subquery) based purely on SQL-92 and three ones (Vertical, GatherJoin, and GatherJoin Variant) based on SQL-OR. We did some performance tests over DB2 for Intelligent Miner and our six approaches using the different sized synthetic generated data sets. Based only on the performance, Cache-Mine is better than SQL-based approach, but it needs additional space to store the data in the local disk. In additional, SQL-based approach can utilize the SQL capability provided by DBMS. But the Cache-Mine does not have this advantage. Everything (including results) is stored in the local disk.

We implemented the mapping of intermediate rule table into the format that the user can understand easily. A visualization module that includes rule table and 3-D

graphics was developed to help the user get the interested information easier through sorting, and filtering functions.

Besides the performance, there are some more differences between Intelligent Miner and our implementation:

- Intelligent Miner can use the data stored in flat file and DB2 database. However, our software can access the data stored in multiple DBMS through JDBC, such as DB2 and Oracle.
- Intelligent Miner can only use the data from one table. However, we can use the data from multiple tables through join/union operation.
- In Intelligent Miner, “Transaction ID” and “Item” has to be a single field. But we extend this ability to process multiple fields. The user can specify which fields are used as “Transaction ID” and which fields are used as “Item”.
- Intelligent Miner uses Directed – Graph as the base of rule visualization technique. As described in Chapter 4, it uses ‘item-item’ relationship so it works well in the situation of few rules. However, our visualization module uses ‘rule-item’ relationship so that it can display more rules at one time. In additional, the rule sorting and filtering ability of our visualization module gives the user more flexibility and efficiency in managing and understanding the association rule.
- Intelligent Miner stores the results in the local disk as flat file. In our implementation, we store the generated rules in the database. Once the rules are stored in database, they can be easily handled because of the SQL capabilities.

6.2 Contributions

In this thesis, we have addressed the following problems.

- Implement three SQL-92 approaches and three SQL-OR approaches using Oracle stored procedures for association rule mining.
- Once the intermediate rule table is generated, map back to the final rule table so that each item has a self-explain name
- Compare the performance of three SQL-92 approaches and three SQL-OR approaches using different sized synthetically generated data sets.
- Conduct the scale-up experiments for our six approaches using different sized synthetically generated data sets.
- Develop a visualization module using Java 3D to help the user manage and understand the association rules.
- Compare our implementation with one of the commercial data mining tools Intelligent Miner in various aspects, such as user interface, input/output, and visualization.

6.3 Future Work

We have identified the following work for future research.

1. In our implementation, although we can access different DBMSs, the data from only one DBMS (either DB2 or Oracle) are used for mining. We plan to provide the user an interface to generate the input data set using the data from all the databases the user specified and apply our mining algorithm to the generated input data set.

2. We plan to extend the existing mining operations. In this thesis, we implemented “association rule” using a series of SQL queries. The next step is to explore the possibility of implement the other mining operations, such as classification and clustering using SQL queries.
3. As to the visualization module, we plan to add more function such as zoom in, zoom out so that the user can have more control over the rules.
4. We plan to explore the possibility of developing some of the operations for association rule as the operators of the database. These operations include SaveTid(), which is used to create the tid list for each item, and $\text{CountAnd}_k()$, which is used to get the number of common elements from k CLOBs, etc. If these operations can be part of the database operators, it will make mining for an association rule easier. Further, we can explore the possibility of developing the whole association rule mining as one operator of the database so that the user only needs to give the DBMS the input table. If this happens, there is no clear boundary of issuing a basic query command and a data mining operation to the user.

APPENDIX
ASSOCIATION RULE MINING EXAMPLE USING KWAY JOIN

This appendix lists one example input data set, the intermediate candidate sets C_x, the intermediate frequent item set F_x, and the final association rules using KWay Join approach with minimum support of 50%, and minimum confidence of 50%.

Input Data Set

We use a small input data set that has 4 transactions (different TID denotes different transactions). Each transaction has 2 or 3 items. The total number of records is 12. Table A-1 shows the items of all the transactions. For example, for the transaction where TID=100, the items are “Milk, Eggs, Bread”.

Table A-1 Example of Input Data Set

TID	ITEM
100	Milk
100	Eggs
100	Bread
200	Sugar
200	Eggs
200	Cake
300	Milk
300	Sugar
300	Eggs
300	Cake
400	Sugar
400	Cake

In order to convert the string format of item to integer format, we generate a "description" table for each item. We can do this by scanning the input data set. For each distinct item, we assign it a distinct number. Table A-2 shows the description table of the example input data set. It has 5 distinct items.

Table A-2 Example of Description Table

ITEM NUMBER	DESCRIPTION
1	Milk
2	Sugar
3	Eggs
4	Bread
5	Cake

The "Mapping" process is to convert all the TID and ITEM from string format to integer format. Based on Table A-1 and Table A-2, the final input data set is generated and stored in database as Table A-3.

Table A-3 TIDITEM Table

TID	ITEM
100	1
100	3
100	4
200	2
200	3
200	5
300	1
300	2
300	3
300	5
400	2
400	5

The rest of this appendix shows all the intermediate results of association rule mining using Kway Join approach for the given data set. We show the multiple passes of support counting phase followed by the rule generation phase.

Support Counting:

There are four passes for the given data set.

First Pass

The candidate set C_1 and frequent item sets F_1 are shown in Table A-4 and Table A-5 respectively.

Table A-4 Table "C_1"

ITEM1
1
2
3
4
5

Table A-5 Table "F_1"

ITEM1	COUNT
1	2
2	3
3	3
5	3

Second Pass

The candidate set C_2 and frequent item sets F_2 are shown in Table A-6 and Table A-7 respectively.

Table A-6 Table "C_2"

ITEM1	ITEM2
1	2
1	3
1	4
1	5
2	3
2	4
2	5
3	4
3	5
4	5

Table A-7 Table "F_2"

ITEM1	ITEM2	COUNT
1	3	2
2	3	2
2	5	3
3	5	2

Third Pass

The candidate set C_3 and frequent item sets F_3 are shown in Table A-8 and Table A-9 respectively.

Table A-8 Table "C_3"

ITEM1	ITEM2	ITEM3
1	2	3
1	2	5
1	3	4
1	3	5
2	3	5

Table A-9 Table "F_3"

ITEM1	ITEM2	ITEM3	COUNT
2	3	5	2

Rule Generation:

Combining the frequent sets of three passes F_1, F_2, F_3, we can get the final frequent sets table FISETS in Table A-10.

Table A-10 Frequent Item Sets "FISETS"

$ITEM_1$	$ITEM_2$	$ITEM_3$	$ITEM_4$	$ITEM_5$	$ITEM_6$	$ITEM_7$	$ITEM_8$	NULLM	COUNT
1	0	0	0	0	0	0	0	2	2
2	0	0	0	0	0	0	0	2	3
3	0	0	0	0	0	0	0	2	3
5	0	0	0	0	0	0	0	2	3
1	3	0	0	0	0	0	0	3	2
2	3	0	0	0	0	0	0	3	2
2	5	0	0	0	0	0	0	3	3
3	5	0	0	0	0	0	0	3	2
2	3	5	0	0	0	0	0	4	2

All of the subsets of each record in table FISETS are generated and stored in table "Primary-Rules". The records of table "Primary-Rules" are shown in Table A-11. Using table "FISETS" and table "Primary-Rules", the association rules can be generated and stored in the table "Rules", which is illustrated in Table A-12. Lastly the final association rules can be presented to the user as Table A-13 by joining "Description" and "Rules" tables.

Table A-11 Table “Primary-Rules”

$TITEM_1$	$TITEM_2$	$TITEM_3$	$TITEM_4$	$TITEM_5$	$TITEM_6$	$TITEM_7$	$TITEM_8$	TNULLM	TRULEM	TCOUNT
1	3	0	0	0	0	0	0	3	2	2
3	1	0	0	0	0	0	0	3	2	2
2	3	0	0	0	0	0	0	3	2	2
3	2	0	0	0	0	0	0	3	2	2
2	5	0	0	0	0	0	0	3	2	3
5	2	0	0	0	0	0	0	3	2	3
3	5	0	0	0	0	0	0	3	2	2
5	3	0	0	0	0	0	0	3	2	2
2	3	5	0	0	0	0	0	4	2	2
3	2	5	0	0	0	0	0	4	2	2
5	2	3	0	0	0	0	0	4	2	2
2	3	5	0	0	0	0	0	4	3	2
2	5	3	0	0	0	0	0	4	3	2
3	5	2	0	0	0	0	0	4	3	2

Table A-12 Table “Rules”

$ITEM_1$	$ITEM_2$	$ITEM_3$	$ITEM_4$	$ITEM_5$	$ITEM_6$	$ITEM_7$	$ITEM_8$	NULLM	RULEM	CONF	SUP
1	3	0	0	0	0	0	0	3	2	100	50
3	1	0	0	0	0	0	0	3	2	66.67	50
2	3	0	0	0	0	0	0	3	2	66.67	50
3	2	0	0	0	0	0	0	3	2	66.67	50
2	5	0	0	0	0	0	0	3	2	100	75
5	2	0	0	0	0	0	0	3	2	100	75
3	5	0	0	0	0	0	0	3	2	66.67	50
5	3	0	0	0	0	0	0	3	2	66.67	50
2	3	5	0	0	0	0	0	4	2	66.67	50
3	2	5	0	0	0	0	0	4	2	66.67	50
5	2	3	0	0	0	0	0	4	2	66.67	50
2	3	5	0	0	0	0	0	4	3	100	50
2	5	3	0	0	0	0	0	4	3	66.67	50
3	5	2	0	0	0	0	0	4	3	100	50

Table A-13 Final “Association Rules”

Rule Head	Symbol	Rule Body	Confidence(%)	Support(%)
Milk	=>	Eggs	100	50
Eggs	=>	Milk	67	50
Sugar	=>	Eggs	67	50
Eggs	=>	Sugar	67	50
Sugar	=>	Cake	100	75
Cake	=>	Sugar	100	75
Eggs	=>	Cake	67	50
Cake	=>	Eggs	67	50
Sugar	=>	Eggs, Cake	67	50
Eggs	=>	Sugar, Cake	67	50
Cake	=>	Sugar, Eggs	67	50
Sugar,	=>	Cake	100	50
Sugar,	=>	Eggs	67	50
Eggs, Cake	=>	Sugar	100	50

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BIOGRAPHICAL SKETCH

Hongen Zhang was born on October 27, 1972, in Xinchang county, Zhejiang province, P.R. China. He received his bachelor's degree in forest genetics from Zhejiang Forest College in June 1994. After his graduation, he was admitted to Bejing Forest University in September 1994 and received his Master of Science degree in forest genetics from Beijing Forest University in June 1997.

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