Ontological Frequent Patterns Mining by potential use of Neural Network

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ABSTRACT
Association rule mining has attracted wide attention in both research and application areas recently. The mining of multilevel association rules is one of the important branches of it. Mining association rules at multiple levels helps in finding more specific and relevant knowledge.In most of the studies, multilevel rules will be mined through repeated mining from databases or mining the rules at each individually levels, it affects the efficiency, integrality and accuracy. In this paper, an efficient algorithm named Multi Level Feed Forward Mining (MLFM) is proposed for efficient mining of multiple-level association rules from large transaction databases. This algorithm uses Feed Forward Neural Networks as Neural networks have been successfully applied in a wide range of supervised and unsupervised learning applications. neural networks have high acceptance ability for noisy data and high accuracy and are preferable in data mining. So we have used supervised neural network in parallel for finding frequent itemsets at each concept levels in only single scan of database.

General Terms
Data mining, association rules, multiple-level association rules, support, confidance.

Keywords
Non-uniform support, Multilayer Perceptron network, frequent itemsets , algorithms, Neural Network

1. INTRODUCTION
Data mining extracts implicit, previously unknown, and potentially useful information from databases. The discovered information and knowledge are useful for various applications, including market analysis, decision support, fraud detection, and business management. Particularly interesting are association rules that reflect relationships among items in datasets. Recall that, in general, associations[1, 2, 4] express specific semantics in linking data items together in the sense that if X →Y is such an association then "occurrence of X is associated with occurrence of Y", where X and Y are attributes of data items.

Ontological association rule mining works in two different processes. First of all it finds frequent items at multiple levels and then on the basis of these frequent items it generate association rules. The first requirement can be full filled by providing concept taxonomies from the primitive level concepts to higher level. User will provide minimum support and confidence, if minimum support and minimum confidence thresholds at each level are uniform then it may lead to some undesirable result. Because, to find data items at multiple level under the same minimum support and minimum confidence thresholds will not give the desirable result. For example there is a hierarchy in which at level 0 there is food, at level one there are bread, milk and fruit and at level 2 we further put the various brands of these items. Large support is more likely to exist at high concept level such as bread and butter rather than at low concept levels, such as a particular brand of bread and butter. Therefore, if we want to find strong relationship at relatively low level in hierarchy, the minimum support threshold must be reduced substantially.

To remove this problem one should apply different minimum support to different concept levels. This leads to mining interesting association rules at multiple concept levels, which will find nontrivial, informative association rules because of its flexibilities for focusing the attention to different sets of data and applying different thresholds at different levels [3].

Association rule mining has a wide range of applicability such Market basket analysis, Medical diagnosis/ research, Website navigation analysis, Homeland security and so on. Association rules are used to identify relationships among a set of items in database. These relationships are not based on inherent properties of the data themselves (as with functional dependencies), but rather based on co occurrence of the data items. Association rule and frequent itemset mining became a widely researched area, and hence faster and faster algorithms have been presented. [5]

Maximum number of approached used so far for the mining of multiple level association rules, are based on Apriori approach, which required more number of operations for counting pattern supports in the database.To reduce number of scans to the database we have applied Supervised neural network to count number of frequent itemsets at each level. This approach combines a level wise top-down traversal in order to quickly find the maximal frequent patterns. A new algorithm MLFM is proposed which works on top-down progressive deepening method by extension of some existing algorithms for mining multi-level association rules. The method finds candidate itemsets at each level and on the basis of minimum support value finds frequent itemsets it will filter the table, which will reduce the size of the database. By using concept of key pattern it reduces database passes at each concept level.

2. MULTIPLE-LEVEL ASSOCIATION RULES

A new approach for mining ontological association rules is proposed in this section, which is based on totally new method of implementing multiple perceptron network in multiple level association rule mining. This algorithm uses a hierarchy information encoded transaction table instead of original table. This is based on the following consideration. First collect the relevant set of data and then work repeatedly on the task related set. Second, encoding can be performed during the collection of task related data and thus there is no extra encoding pass required. Third, an encoded string, which represents a position in a hierarchy, requires lesser bits than the corresponding actual values. Thus, it is often beneficial to use an encoded table. In MLPN algorithm We find frequent itemsets at all the levels in parallel fashion, thus a perceptron network is created for all the levels. As data is read from the database, it is being given as a input to the multilayer feed forward neural network, according to the level of hierarchy. Data at all the levels is given as input by scanning the databse only once, and thus produces fast output.

Example : Suppose that a shopping transaction consist of First. A sale item description table (Table :1) which consist of a set of attributes Item code, Category, Type, Material, Style and Second. A sales transaction table(Table :- T1) which consist of transaction number and set of items purchased.

Sales item description table:

Table 1

Code	Category	Type	Material	Style
1001	Bed	Single	Steel	Without Box
1002	Sofa	3 sitting	Wood	Small
---	--	--	--	---
---	--	--	--	---

A Sales Transaction table T1:-

Transaction Id	Code
134876	{1001,1002,2001,2003,...}
234760	{2001,2004,40292,3984...}
--- --- --- --- --- ---	--- --- --- --- --- ---
--- --- --- --- --- ---	--- --- --- --- --- ---

As we said above, the taxonomy information for each (grouped) item is encoded as a sequence of digits in the transaction table (Table). The items are encoded as follow for example “6111” means “Bed, Single, Made of Iron, With Box” in which Digit ‘6’represents ‘Bed’ at level 1, digit ‘1’ represent ‘Single’ at level 2, digit ‘1’ represent ‘Iron’ at level 3 and last digit ‘1’ represent ‘With Box’ at level 4.

Previous studies on data mining focused on finding association rules at a single concept level. Mining association rules at multiple concept levels may, however, lead to discovery of more general and important knowledge from data. Relevant item taxonomies are usually pre defined in real-world applications and can be represented as hierarchy trees. Terminal nodes on the trees represent actual items appearing in transactions; internal nodes represent classes or concepts formed from lower-level nodes . A simple example is given in Figure 1.

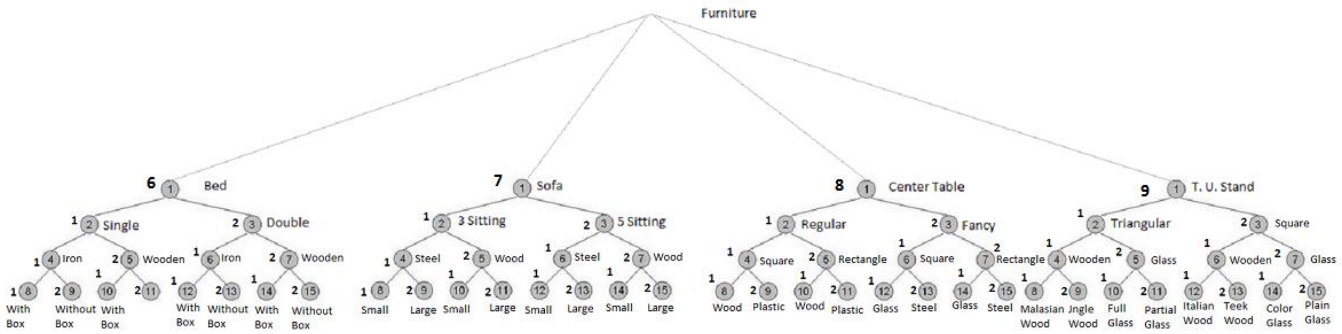


Figure. 1

In Figure 1, the root node for “Furniture” is at level 0, the internal nodes representing categories (such as “Bed”,”Sofa” etc.) are at level 1, the internal nodes representing Types of furniture (such as “Single”, ”Double ”) are at level 2, the nodes representing material (such as “Iron”,”Wooden”) are at level 3, and terminal nodes represent size of furniture is at level 4. Han and Fu proposed a method for finding level-crossing association rules at multiple levels [6]. Their method could find flexible association rules not confined to strict, pre-arranged conceptual hierarchies. Nodes in predefined taxonomies are first encoded using sequences of numbers and the symbol “*” according to their positions in the hierarchy tree [7]. For example, the internal node “Bed” in Figure 1 is represented by 6***, the internal node “Single” by 61**, the level 3 node by 611*, and the terminal node “With Box” by 6111. A top-down progressively deepening search approach is used and exploration of “level-crossing” association relationships is allowed [8].

In figure 1, we are considering the example of Furniture items, the root node i.e. “Furniture ” is at level 0. The process discovers the frequent patterns and strong association rules at the top most concept level. At the first level, let the minimum support at this level is 5%. And the minimum confidence be 50%. We may find, a set of frequent item sets at level 1 or frequent 1 itemsets or single frequent itemsets with their support in parenthesis like, bed(25%) , sofa(30%),Centre Table(28%), TV Stand(45%). At level 1, frequent two itemsets or a set of pair wised frequent items also called frequent 2 itemsets would be combination of more than one item sets at level 1 i.e. (bed, sofa (20%)),(bed, centre table(24%)) ,(bed,Tv Stand(32%)),(sofa,Center table(35%)),(sofa,Tv Stand(28%)) ,(Centre table,Tv Stand(26%)) . Frequent three itemsets or set of paired wise frequent 3 itemsets shall be, (bed, sofa, center table(24%)),(bed,sofa,tv stand(28%)),(sofa,centre table, tv stand). And Level 1 frequent four itemsets shall be combination of all items at level 1 i.e(bed,sofa,center table, Tv stand(8%)). And a set of strong association rules, such as bed=>sofa(60%),bed=>sofa,center table(58%) etc will be produced.

At the second level, let the minimum support at this level is 4%. And the minimum confidence be 40%. We may find, a set of frequent 1 item sets at level 2 or Level 2 frequent 1 itemsets with their support in parenthesis like (bed, single(25%)) , (bed,double(20%)), (sofa, 3 sitting (30%)),(sofa, 5 sitting(24%)),(Centre Table, Regular (28%)), (Centre Table, Fancy (22%)), (TV Stand, rectangle (30%)), (TV Stand,triangular(33%)). Level 2 frequent 2 itemsets will be ((bed, single), (sofa, 3 sitting)(25%)),((bed, single), (sofa, 5 sitting)(20%)), ((bed, double), (sofa, 3 sitting(30%))......(Centre Table, Fancy),(TV Stand, triangular(33%))...etc.The process repeats at each lower concept level until no frequent patterns can be found.

Illustration of the diagram is as follows:-

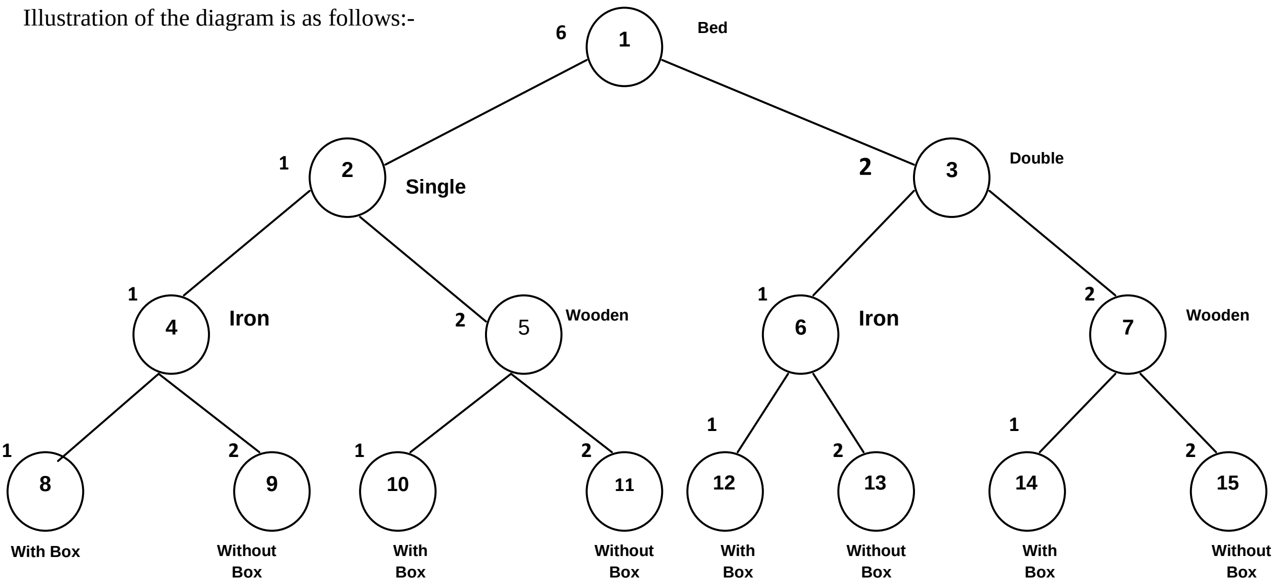


Figure 2

3. NEURAL NETWORK METHOD IN DATA MINING

Neural network method[9] is used for classification, clustering, feature mining, prediction and pattern recognition. It imitates the neurons structure of animals, bases on the M-P model and Hebb learning rule, so in essence it is a distributed matrix structure. Through training data mining, the neural network method gradually calculates (including repeated iteration or cumulative calculation) the weights the neural network connected. The neural network model can be broadly divided into the following three types:

(1) Feed-forward networks: it regards the perception back-propagation model and the function network as representatives, and mainly used in the areas such as prediction and pattern recognition;

(2) Feedback network: it regards Hopfield discrete model and continuous model as representatives, and mainly used for associative memory and optimization calculation;

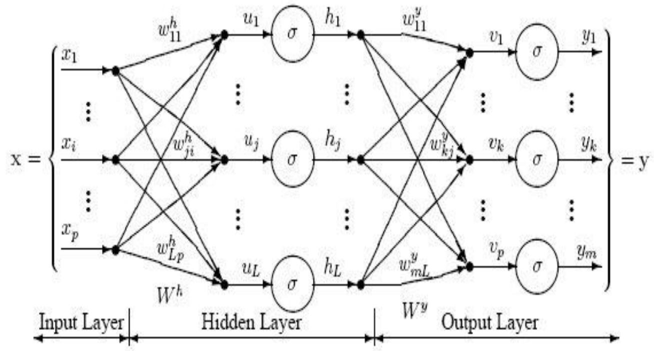
(3) Self-organization networks: it regards adaptive resonance theory (ART) model and Kohonen model as representatives, and mainly used for cluster analysis.

3.1 Feedforward Neural Network :

Feed forward neural network are the most popular and most widely used models in many practical applications. They are known by many different names, such as "multi-layer perceptrons."

The Multilayer Perceptron Neural Network Model

The following diagram illustrates a perceptron network with three layers:



This network has an input layer (on the left) with three neurons, one hidden layer (in the middle) with three neurons and an output layer (on the right) with three neurons.

There is one neuron in the input layer for each predictor variable. In the case of categorical variables, *N*-1 neurons are used to represent the *N* categories of the variable.

Input Layer — A vector of predictor variable values ($x_1...x_p$) is presented to the input layer. The input layer (or processing before the input layer) standardizes these values so that the range of each variable is -1 to 1. The input layer distributes the values to each of the neurons in the hidden layer. In addition to the predictor variables, there is a constant input of 1.0, called the *bias* that is fed to each of the hidden layers; the bias is multiplied by a weight and added to the sum going into the neuron.

Hidden Layer — Arriving at a neuron in the hidden layer, the value from each input neuron is multiplied by a weight (w_{ji}), and the resulting weighted values are added together producing a combined value u_j. The weighted sum (u_j) is fed into a transfer function, σ, which outputs a value h_j. The

outputs from the hidden layer are distributed to the output layer.

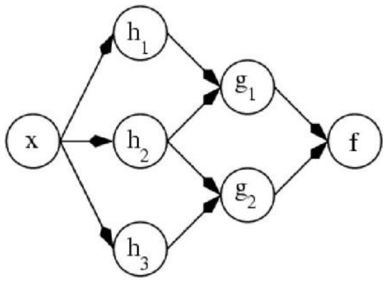
Output Layer — Arriving at a neuron in the output layer, the value from each hidden layer neuron is multiplied by a weight (w_{kj}), and the resulting weighted values are added together producing a combined value v_j. The weighted sum (v_j) is fed into a transfer function, σ, which outputs a value y_k. The *y* values are the outputs of the network.

If a regression analysis is being performed with a continuous target variable, then there is a single neuron in the output layer, and it generates a single y value. For classification problems with categorical target variables, there are *N* neurons in the output layer producing *N* values, one for each of the *N* categories of the target variable.[9]

3.2 Multilayer Perceptron Architecture

The network diagram shown above is a full-connected, three layer, feed-forward, perceptron neural network. "Fully connected" means that the output from each input and hidden neuron is distributed to all of the neurons in the following layer. "Feed forward" means that the values only move from input to hidden to output layers; no values are fed back to earlier layers (a Recurrent Network allows values to be fed backward).

All neural networks have an input layer and an output layer, but the number of hidden layers may vary. Here is a diagram of a perceptron network with two hidden layers and four total layers:



When there is more than one hidden layer, the output from one hidden layer is fed into the next hidden layer and separate weights are applied to the sum going into each layer.

3.3 A Method for Mining Multiple - Level Association Rules

In this section a new approach for mining multiple level association rules is proposed, which is based on new method of implementing multiple perceptron network in multiple level association rule mining. [10][11][12][13]

Transaction Table :

Transactions	Orders
T1	6111, 6112, 6121, 6122
T2	6121, 6211, 6222, 7111, 8211, 9122
T3	6111, 6122, 7112, 7121, 8121, 9212
T4	6112, 6122, 7121, 7221, 9111
T5	6211, 7221, 7231, 8121, 8211, 9121
T6	7221, 8112, 8121, 8211, 9211
T7	7222, 8211, 8212, 9112
T8	8112, 8211, 8212, 9111
T9	8112, 8121, 8212, 9121
T10	8211, 9121, 9212, 9222
T11	6122, 7211, 8121, 9122
T12	6211, 7222, 8211, 9211

The extraction of frequent itemsets at level-1 works as follows. Let the minimum Support at level 1 be 60%. The level-1 frequent 1-itemset table freq[1,1] can be derived by scanning transaction table T1,registering support of each generalized item, such as 6***,7*** …….., n***, if a transaction contains such an item (i.e., the item in the transaction belongs to the generalized item I***, ..., n***, respectively.

Level-1, Frequent 1 Itemsets Min support = 5	
Item	Frequency
6***	7
7***	8
8***	9
9***	11

Frequent 1 items at level-1

Level 1, frequent 2 itemsets Min Support = 5	
Item	Frequency
6***, 7***	6
6***, 8***	5
6***, 9***	6
7***, 8***	5
7***, 9***	8
8***, 9***	9

Frequent 2 items at level-1

Level 1, frequent 3 itemsets Min Support = 5	
6***, 7***, 8***	5
6***, 7***, 9***	6
6***, 8***, 9***	5
7***, 8***, 9***	7

Frequent 3 items at level-1

Level 1, frequent 4 itemsets , Min Support = 5	
Item	Frequency
6***, 7***, 8***, 9***	5

To address this problem we have used Multilayer Perceptron Architecture, in which database is scanned transaction by transaction and items are read one by one. For items at level 1 of the concept hierarchy, an order at the first position of the transaction is read and its first component i.e. item present at Level 1 of the concept hierarchy shall be given as an input to the first multilayer perceptron network.

It works as follows:-

The algorithm reads first order code in Transaction T1, the first element of this order code i.e. element 6*** is given as an input to the first node of the perceptron network. Once an item code is being read from the transaction say transaction T1, then it is not read again from other item codes present in the same transaction id. The algorithm searches for other item codes present in the Transaction id., and keep on updating the perceptron network according to presence of items. (i.e presence of 7***,8***,9***). And thus create the Input Layer of the perceptron network.

The output of input layer becomes the input of the first hidden layer, and thus according to presence of items at input layer, combinations of frequent 2 itemsets at level 1 is created, and its frequency is updated accordingly. Since all the items at level 1 are frequent, the level-1 frequent 2 itemsets freq[1,2] will be combination of all items with each other i.e. {6***, 7***}, {6***, 8***},{6***, 9***},{7***, 8***},{7***, 9***}, and {8***, 9***}

The output of first hidden layer becomes the input of the second hidden layer, and thus according to presence of items at first hidden layer, combinations of frequent 3 itemsets at level 1 is created, and its frequency is updated accordingly. Although all the items at level 2 are frequent , the level-1 frequent 3 itemsets freq[1,3] will be created according to the formation rule that freq 3 itemset is created by the combination of those freq 2 itemsets which are frequent and whose prefixes are same i.e. {6***, 7***,8***}, {6***, 7***,9***},{6***, 8***,9***} and {7***, 8***,9***}.

The output of second hidden layer creates the output layer of the perceptron network, and it is the

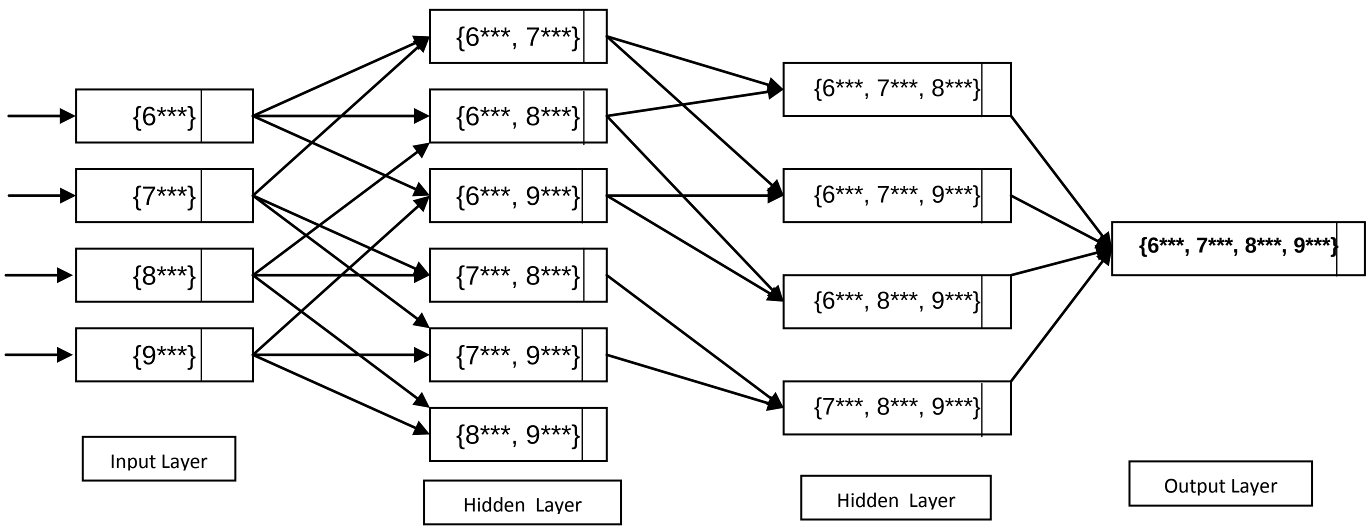


Figure 3

combination of all the items present at hidden layer 2 i.e. {6***,7***, 8***,9***}.

According to the definition of multiple-level association rules, only the descendants of the large items at level-1 (i.e., in freq[1,1]) are considered as candidates for the level-2 large 1-itemsets. Let minsup[2] =4. The level-2 large 1-itemsets freq[2,1] can be derived from the transaction table T by accumulating the support count and removing those whose support is smaller than the minimum support, which results in freq[2,1].

Frequent 1 items at level-2

Level 2, frequent 1 itemsets Min Support = 4	
Item	Frequency
61**	5
62**	3
71**	3
72**	6
81**	6
82**	7
91**	7
92**	2

The algorithm reads first order code in Transaction T1, the first two elements of this order code i.e. element 61** is given as an input to the first node of the perceptron network. Once an item code is being read from the transaction say transaction T1, then it is not read again from other item codes present in the same transaction id. The algorithm searches for other item codes present in the Transaction id., and keep on updating the perceptron network according to presence of items. (i.e presence of 71**,81**,91**). And thus create the Input Layer of the perceptron network.

The output of input layer becomes the input of the first hidden layer, and thus according to presence of items at input layer, combinations of frequent 2 itemsets at level 2 is created, and its frequency is updated accordingly. Since five items are frequent at level[2,1], the level-2 frequent 2 itemsets freq[1,2] will be combination of all frequent items at level 1, i.e. {61**, 72**},{61**, 81**},{61**, 82**},{61**, 91**}, {72**, 81**} , etc.

Level 2, Min Support = 4, frequent 2 itemsets	
Item	Frequency
61**, 72**	2
61**, 81**	2
61**, 82**	1
61**, 91**	3
72**, 81**	3
72**, 82**	3
79**, 91**	4
81**, 82**	3
81**, 91**	4
82**, 91**	5
72**, 91**	4
81**, 91**	4
82**, 91**	5

Frequent 2 items at level-2

Since there are only four frequent itemsets that qualify the min support criteria, and these four frequent itemsets cannot be joined to calculate frequent 3 itemsets at level 2 i.e. freq[2,3] because there prefixes are not same. Thus this levels frequent itemsets count stops here.

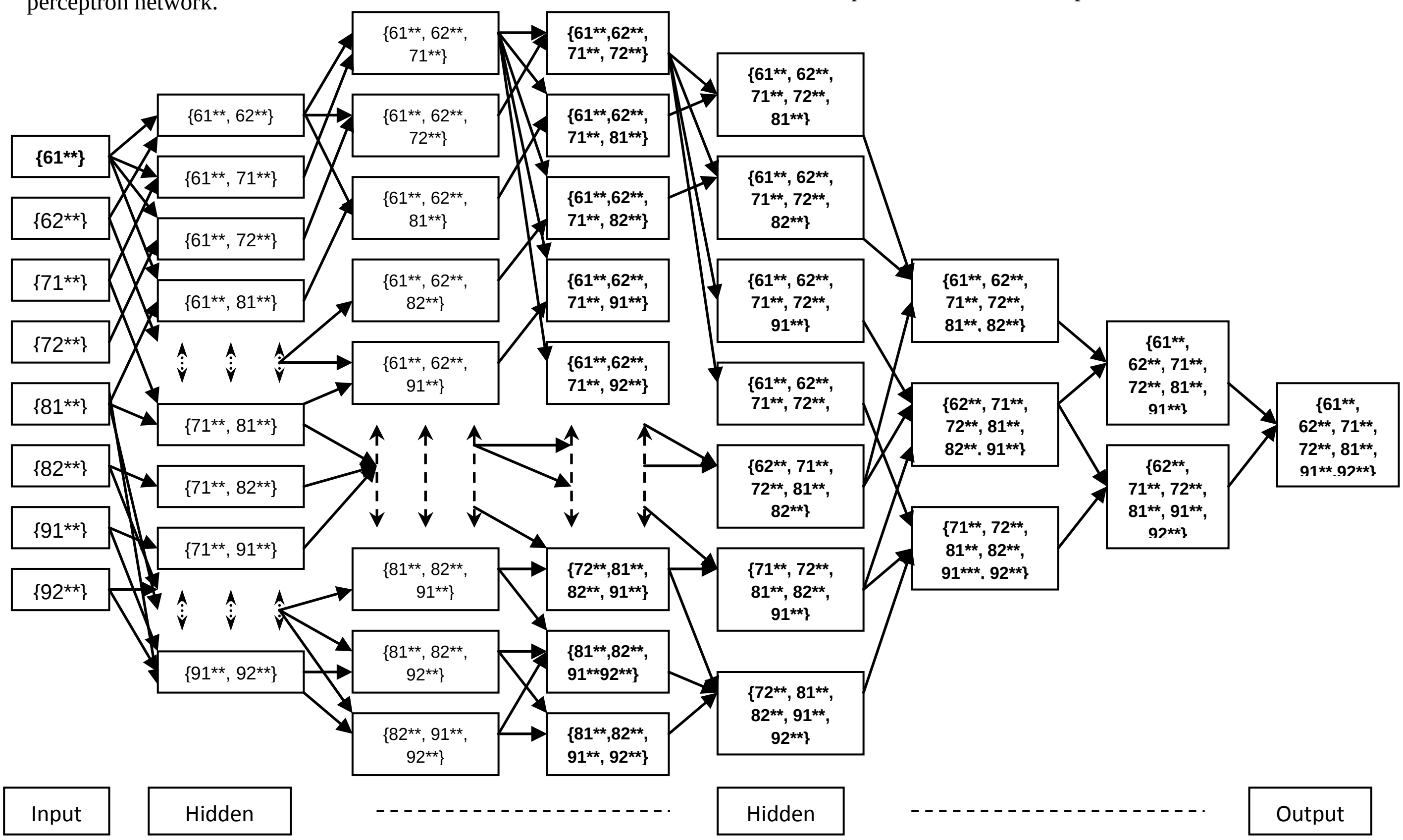


Figure 4

Likewise, the frequent itemsets at level 3 will be generated as :-

Level 3, Min Support = 3, frequent 1 itemsets	
Item	Frequency
611*	3
612*	4
621*	3
622*	1
711*	2
712*	2
721*	1
722*	5
811*	3
812*	5
821*	7
822*	0
911*	3
912*	5
921*	4
922*	1

Similarly, the frequent 2-itemset table freq[3,2] is formed by the combinations of the frequent entries in freq[3,1].

Level 3, frequent 2 itemsets, Min Support = 3	
Item	Frequency
611*, 612*	3
611*, 621*	0
611*, 722*	1
611*, 811*	0
611*, 812*	1
611*, 821*	0
611*, 911*	0
611*, 912*	0
611*, 921*	1
612*, 621*	1
612*, 722*	0
612*, 811*	0
612*, 812*	2
612*, 821*	1
612*, 911*	1
612*, 912*	1
612*, 921*	0
621*, 722*	2
621*, 811*	0
621*, 812*	1
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811*, 912*	1
811*, 921*	1
812*, 921*	2
821*, 911*	0
821*, 912*	1
821*, 921*	2
911*, 912*	1
911*, 912*	4
911*, 921*	2
912*, 921*	0

To implement this problem using Multilayer Perceptron Architecture, in which database is scanned transaction by transaction and items are read one by one, again we have **(See. Figure 5)**

The algorithm reads first order code in Transaction T1, the first three elements of this order code i.e. element 611* is given as an input to the first node of the perceptron network. Once an item code is being read from the transaction say transaction T1, then it is not read again from other item codes present in the same transaction id. The algorithm searches for other item codes present in the Transaction id., and keep on updating the perceptron network according to presence of items. (i.e presence of 612*,621**...711*.. etc).[11] And thus create the Input Layer of the perceptron network of third level.

Since there are only four frequent itemsets that qualify the min support criteria, and these four frequent itemsets can not be joined to calculate frequent 3 itemsets at level 2 i.e. freq[2,3] because there prefixes are not same. Thus this levels frequent itemsets count stops here.

The level-4 large 1-itemsets freq[4,1] can be derived from the transaction table T by accumulating the support count and removing those whose support is smaller than the minimum support, which results in freq[4,1] in table 4.1

Table 4.1

Level 4, Min Support = 3, frequent 1 itemsets	
Item	Frequency
6122	4
6211	3
8112	3
8121	5
8211	4

The level-4 large 2 -itemsets freq[4,2] can be derived from the transaction table 4.1 by accumulating the support count and removing those whose support is smaller than the minimum support, which results in Table 4.2, which has only one frequent itemset i.e {6211, 8211}. Thus the Neural Network generated for level 4 frequent itemsets(see figure-6) stops working after level 4 frequent 2 itemsets.

Level 4 frequent 2 itemsets(Table 4.2)

Level 4, Min Support = 3, frequent 2 itemsets	
Item	Frequency
6122, 6211	0
6122, 8112	0
6122, 8121	2
6122, 8211	0
6211, 8112	0
6211, 8121	1
6211, 8211	3
8112, 8121	2
8112, 8211	2
8121, 8211	1

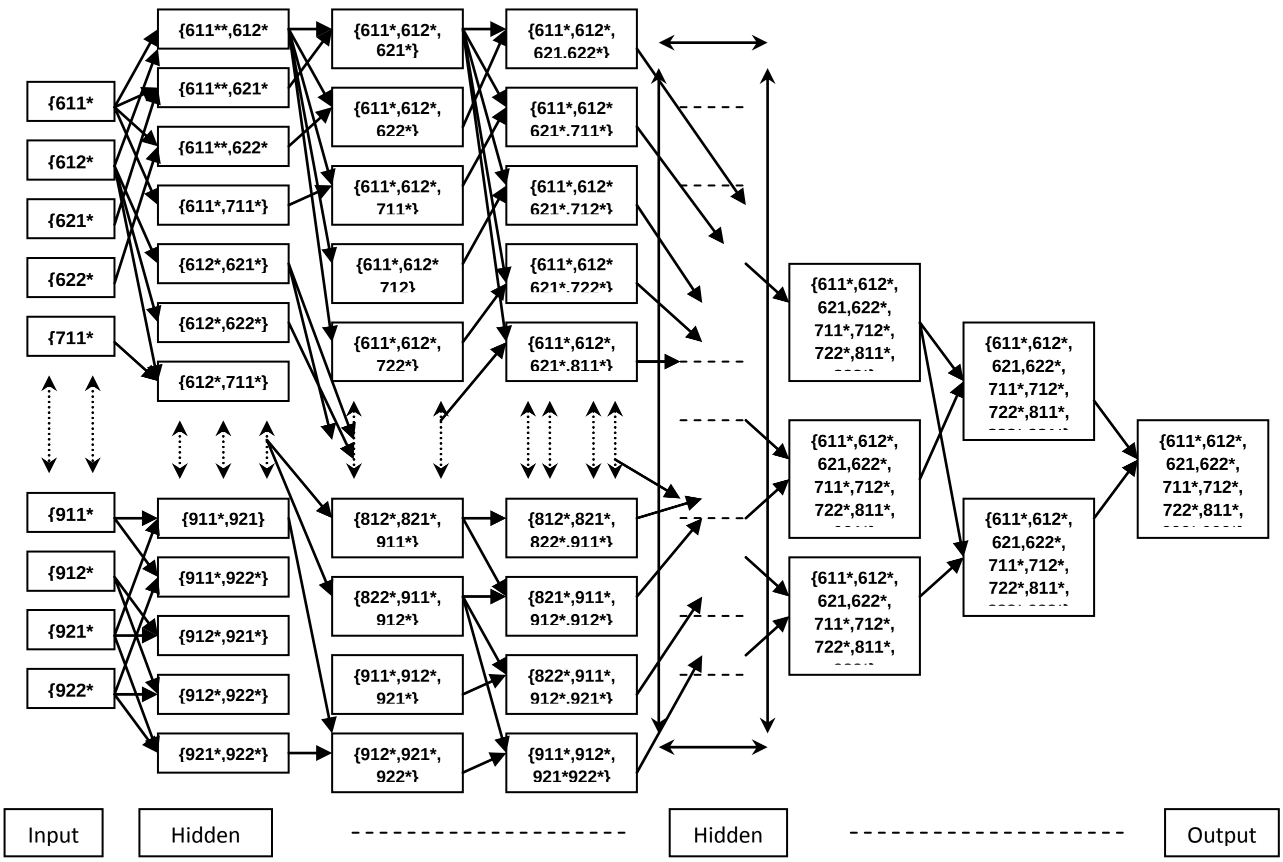

Figure 5

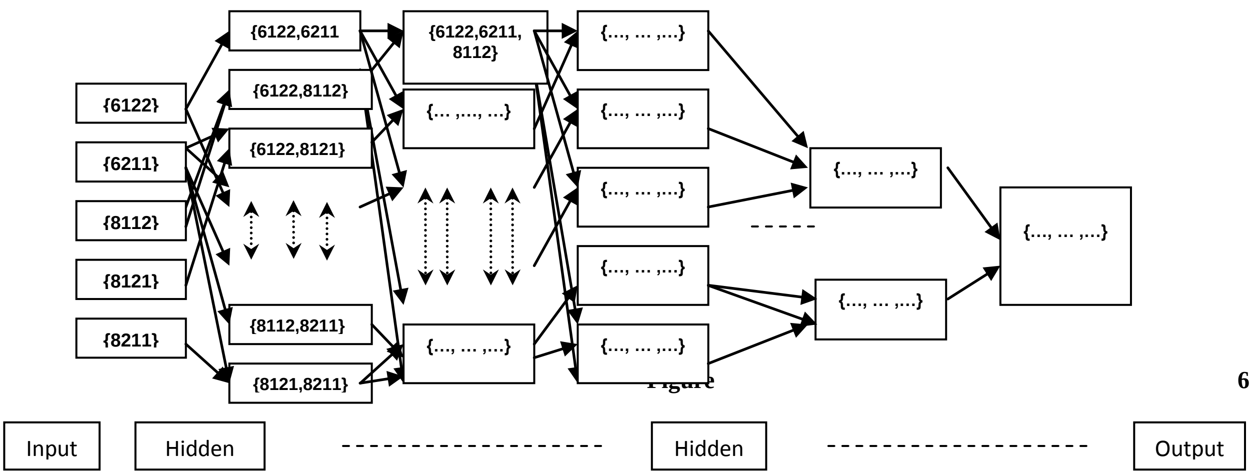

Figure 6

4. ALGORITHM 1 MLFM

Input:-

T[1], a hierarchy information encoded and task relevant set of transaction database, in the form of <TID, itemset> in which each item in the itemset contains (1) encoded concept hierarchy information and (2) the minimum support threshold (minsup[l]) for each concept level l.

Output: -

Separate items present at different levels of hierarchy.

Method:-

A top down progressively deepening process which collects large item sets using multilayer perceptron network is as follows

1. For(l=1;L[l,1] = 0) and l < max_level;l++)
2. {
3. Z = Read total number of items at level l.
4. N = Read total number of barcode items in a transaction
5. For(n = 1; n<N; n++)
6. {
7. M = Calculate total number of levels
8. K = Read n^{th} item of transaction
9. For(m = 1 ; m <= M; m ++)
10. {
11. K = Separate m^{th} term(s) from the first item using Modulus operator.
12. Insert_to_NNm(K,Z)
13. }
14. }
15. }

4.1 Algorithm2 Insert_to_NNm(K,Z)

Input:-

K, a extracted information from the transaction database in the form of <ItemPresent, total no.of items at level l >in which each Item Present represents (1) item present at concept level 1 to concept level n in the form of item at single level, double level, triple level and so on. And (2) total number of items at different levels of the hierarchy so that the multilayer perceptron network can be drawn.

Output:-

Multilevel frequent itemsets

Method:-

A process to insert items parallely in the multilayer perceptron neural network. It works as follows : -

1. For(i = 1; i < Z ; i ++)
2. {
3. Caclulate $^{Z}C_i$
4. Insert K1 to the corresponding node at level i;
5. Update frequency of node [K1] to 1 and update frequency of rest of the nodes to Zero.
6. Create next level of the perceptron network by combining elements of last level i.e. level2 = l1xl2, l1xl3,l1xl4....lnxlm(if combination of items is possible)
7. }

5. EXPLANATION OF ALGORITHM 1

The algorithm works as follows: At level 1 (l =1), the algorithm reads total number of items at level 1, total number of barcode items in transaction 1 and the total number of levels in the hierarchy tree. Algorithm starts reading data in transaction 1 i.e. first barcode item present in the transaction, then it separates the first item of the item code by applying modulus operator at the item code and supplies it to the Insert_to_NNm algorithm

This algorithm works in parallel fashion as when it separates first term of a item the term which is generated is a item present at the first level of the hierarchy tree and it is passed to the first Neural Network as its argument to calculate the frequent items at first level. When algorithm separate first two terms of the barcode and it is passed to the second Neural Network as its argument to calculate the frequent items at second level of the hierarchy tree and the process is same for the n^{th} level of the hierarchy tree.

5.1 Explanation of Algorithm 2 :-

The algorithm works as follows:- Algorithm 1 passes first term of the bar code item at transaction 1 and the total number of items present at that level as an argument to the Algorithm 2. Algorithm 2 calculates the combination of the series by formula nCr and with the help of Z value passed by the algorithm 1, and calculates the total number of items present at the first level or input level of the perceptron network. And thus creates a complete neural network. Input K goes as an input of the first layer and updates frequency of the respective node by 1 whereas updates frequency of other nodes by 0. This process is repeated for all levels or layers of the perceptron network and thus creates frequent 1 items at all levels of the hierarchy tree. If the (argument) item passes by the algorithm 1 is of two terms then the input is passed to the second neural network and so on.

Thus by reading transaction database only once and by giving its values to different perceptron networks as an input the MLDM algorithm generates the frequent large itemsets of multiple level hierarchy tree.

6. CONCLUSION

We have extended the scope of the study of mining association rules among from concept at the same level of a hierarchy to concept of different level of hierarchy in multiple concept levels and develop new method of mining multi – level association rules by applying multi level perceptron neural network. This new efficient top-down progressive deepening technique incorporate counting of frequent itemsets at each level of the concept hierarchy. At each level it reads items once and divide them according to different levels of concept hierarchy and passes it to the neural network to generate frequent itemsets. Due to this it reduces the number of database passes, and it scans the database only once. It saves substantial amount of processing. Thus it will be a promising algorithm in these circumstances.

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