Optimizing Predictive Modelling of Customer Behaviour Using Simulated Annealing

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ABSTRACT

Customer behaviour modelling is an important data mining approach for making operational and strategic decisions. Market Basket Analysis (MBA) is used to determine products that customers purchase together. Knowing the products that a customer will shop as a group is very helpful to a retailer. The business can use this information in predicting sales at the right time, at the right place, and for the right customer. Moreover, Company Marketers can use the basket analysis results to determine new products to serve their existing loyal customers. In the present paper, Genetic Algorithm is used to determine the population of solutions, which consumes more time to produce a solution. In this paper, it is proposed to use the Extended HCleaner Algorithm to remove noisy data from the datasets. The pre-processed dataset is then submitted to an ANN model. From the ANN model, weights of the products are determined by an association. The products which get maximum weights are sent to *Apriori* algorithm, which calculates the optimal combination of the products. The solution of *Apriori* algorithm is sent to next level of the predictive model. It contains two stages: (1) Similarity calculation through cosine similarity technique and (2) Simulated annealing. The cosine similarity is used to obtain the association between products which is further sent to simulated annealing algorithm to find the single solution through association rules. Simulated annealing is used to minimize the response time. It is more effective than the existing system.

Keywords: Association Rule Mining, Market Basket Analysis, Predictive Modelling, Simulated Annealing, Similarity Technique

1. INTRODUCTION

Market Basket Analysis is one of the data mining tools used to discover the co-existence or co-occurrence of the categorical or nominal observations. Market Basket Analysis is used to recognize purchasing patterns of the customers in the retail market with the relevant level of transactional data. But, it remains very hard to get valuable information that was hidden in large databases. So the proposed approach uses the novel technique to reduce such difficulties.

Simulated annealing is a method for finding a single solution to an optimization problem. If you want to maximize or minimize product quantity, your problem can be solved with simulated annealing. The Traveling Salesman Problem is a famous example for optimization problem [1] [22] [23] [25].

A GANN approach was utilized to forecast of short term hourly electricity price and this resulted to be compared with ANN (Artificial Neural Network). The simulation for prices of electricity over 24 hours by the method of NN, and such led to 24 outputs. It was done by three layers, an input and an output layer, and one hidden layer [2]. A network sigmoid function was presented which is utilized to be function for activation. A neurons in hidden layer are allowed to be in the form of neural networks were detected in a features and captured in data patterns. This performed the non-linear mapping between input and also the output variable. Such resulted are achieved in simulation which predicts to offer the improved and exact results [21] [3].

A wide application of distributed system of information is provided with a structure of larger data in the shopping mall, departmental stores etc. These collections of data are enclosed with healthy information that required to be discovered. Businesses can learn from their transaction data more about the activities of their customers and thus can enhance their business by using this knowledge. External information of about the market stocks and the estimation of its performances in Web robot are presented in [1].

The selection of optimal attribute on the subset based on the correlation with the use of Genetic Algorithm, in which GA was used as an optimal search for the fitness values. The correlated attributes are strong that cannot be a part of data warehouse; such attributes are fit be part of crossover operations, which are with lower correlation in coefficients. It optimized in features subset of the hyper spectral data and the parameters of SVM kernel in a similar manner and hence finally achieved higher with classification accuracy [5].

It aims at reduction of stocks information to be increased in efficiency and also in the accuracy of prediction. It gave solution for the problem of stocks analyzing with the financial aspects, which are applied widely in the various business. A determination of system for the prediction of prices of the stock depends on the centralized Web robot distributive system by the construction of SVM and GA.

This intended to minimize of differences between stocks and hence selects a similar range to present the industry news or stock news. Thus, the final outcomes showed a good performance. The demonstration based on network approach was isolated with an influence of products, search mitigation through the large massive lists of association rules. The measure for interestingness was developed in the communities of products. This resulted on networks to be built with products for propose of analysis in the strategy with the combination of both network and traditional based techniques [2].

The market basket analysis technique for integration of word segmentations and the mining of association rules are presented. The items characteristics are made in automatic manner before the mining of association rules are done with word segmentations. Such method was applied to restaurant that was equipped with an electronic ordering method for the recommendations to the customers. This was resulted that method was valid and efficient [4].

A condition was a traditional technique was identified with patterns of purchasing in multi-store environment. Such approach used an adaptive association rule mining technique with the Faster Rule Generation for the Market Basket Analysis. It helped customers for purchasing their products with comfort that results in rise of products sales. This was achieved with confidence of rules weighted and also with sufficient combination of comparison among active user and rules [22] [6].

A Genetic and a Particle Swarm Optimization technique were approached in market basket analysis sample. It is generated that if a data set is larger and in order to get rules in a short period, PSO was a good key to be enhanced, but the efficiency or in case of optimal solution, a Genetic Algorithm was a better solution. The rules that are generated were very efficient since they are formed in filtering. The process of comparing datasets sample and datasets rules helps to analyze for various decisions to improve productivity for items [5] [7].

The modified genetic algorithm in association of mining rules was presented to perform the chromosomes selections from previous generated chromosomes with good performance and rime consumption. The results specified that rules are selected to produce 10 percent support and the confidence of 60 percent in the reducing time processing [8].

The K- Apriori method was used to produce high frequent item sets and the association rules. A Market Basket Analyses was used to manage goods that are placed in a store. The products which are related were placed together as the customers can able to find items that he/she influences to buy. This increased satisfaction of customers and profit. The association rules are then generated separately to satisfy the specific needs of a customer related to cost. This resulted that market basket analysis with K-Apriori method improved the complete revenue [9].

A solution for optimal product that was made of items are to be minimized by dead stock, the maximized revenue for merchant with a profitable products, and compliance with constraints sets are ensured by choosing the product. The results were provided with ability in converging to the solutions of high fitness, in the occurrence of various constraints [10] [24].

The TS awareness for BDA automation on the ASC with the consideration for the requirements of BDA process was presented. The multivariate optimization technique was reached with minimal resources consumption. The method was flexible and it was assured to BDA automation technique on ASC which was effective to attain a desired goal [12].

The focus on performing with frequent item sets in mining with the use of Apache Spark was studied on based with the FP-Growth and comparing with the Map Reduce technique implementation. The spark performance implementation had high execution speed with grown size of datasets. This was associated with the BigFIM technique through Hadoop. It clearly showed the existence of larger datasets in the Map Reduce method had overcome the problem of latency determinations in the Spark performance [13].

An optimization of convergence in network speed and accuracy were improved in such a way that algorithm was feasible for forecasting of stock for a short-term. An experiments were founded that algorithm had improved in accuracy of network and thus cannot predict an error of optimization for neural network. Stability was verified in randomness of GA that showed stability as very poor. There was gap among practicality and accuracy.

The problem for optimal initial weight and reduce of average error was predicted that every part of genetic algorithm to be strong, which can be adjusted in local algorithm. In variation, a search process does not fell to the local minimum. It was in combination with GA through fitness value calculation and it followed crossover and selection. The mutation solved weights for optimization of network problems [14].

A performance of a GA through neural networks is measured. But, rather with neural networks, SVM also can be supported for the use of optimization. There was major improvement in hybrid performance. Fitness was calculated only after the each process and this was repeated until a fitness value was obtained. A fitness values are new values of weights and a biases [11] [15].

The handling of high data in dimensions is in consideration with domain based and also preferred by user. Researches of unexpected trades which are developing are in accordance to evidences by finding the correlated stocks. With domain, a Sharpe ratio was suggested for fitness calculation of every individual. It covered necessary information about profit and risk of behavior in trade [12] [16].

The algorithm named GA-RBFNN was generated for the STLF. The performance was calculated with MMAPE on loaded data. The results are achieved to show differentiation among FFNN and RBFNN, this was optimized to center width of the RBFs and the weights of output layer in RBFNN which resulted to good accuracy of load. The advantages are reduction in the parameters of input, and optimized center width of activation function of hidden layer and the weights of output layer in RBFNN were resulted [11] [12].

2. METHODOLOGY

The proposed method uses Extended HCleaner Algorithm which that removes the noisy data from the datasets. Then the pre-processed dataset is converted into the ANN model. The weights of the products are determined by the ANN model. The products which have maximum weights are provided as input to *Apriori* algorithm. The cosine similarity is used to predict the association between products which is further sent to Simulated Annealing algorithm to find the single solution through association rules. It is found that Simulated Annealing minimizes the response time. It is more effective than the existing system.

Step by step procedure to develop the proposed predictive model is as follows:

- Removing noisy data through data cleaning
- Calculate weight of dataset
- Select maximum weight product
- Predictive model based on Similarity calculation
- Predictive model based on Simulated Annealing

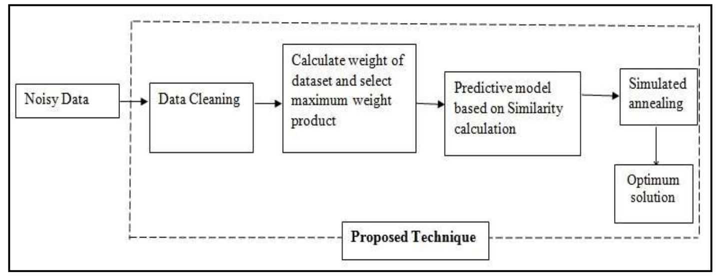

Figure 1: Proposed technique

Dataset Description:

The dataset used for the experiment is collected from the Salem Marafi repository. It contains 9835 rows, which is the combination of various products that customers have purchased in a single shopping trip. Here, the dataset represents the set of shopping transactions and the items purchased. Each row is called as a transaction and each column in a row represents an item purchased.

The items in an itemset are represented as follows:

$V = \{v_1, v_2, \ldots, v_n\}$

Where, $v_1, v_2, \ldots v_n$ are different items

A shopping transaction is represented as follows:

$S_n = \{s_j, s_k, \ldots, s_n\}$

Here, S_n is a set of transactions.

An Association rule is represented as follows:

$\{v_1, v_2\} \Rightarrow \{v_k\}$

For example,{ coffee, sugar} => {milk}

2.1 Data Cleaning

Data cleaning is an important phase in data analysis, which removes the noisy data from dataset and in turn, improves the quality of Market Basket Analysis. The proposed technique provides an Extended HCleaner Algorithm for removing the noisy data. It scans the complete dataset in a single pass and locates the unwanted noisy data from the dataset. Finally the proposed technique removes the noisy data [20] from the dataset. This cleaned data is further sent to similarity calculation based predictive model [17] to obtain better result. The data cleaning algorithm for the proposed technique is described below:

Algorithm 1: Extended HCleaner Algorithm (E-HCleaner)

```
Data: Transaction set T, Noise fraction Ɛ, Radius r
Result: Set of noise objects N, Set of non-noise objects P
for  i = 1 to ntrans do
        if T[i].contain(HTMLcharcters) then
                T[i].remove(HTMLcharacter)
        end
        if T[i].contain(StopWords) then
                T[i].remove(StopWords)
        end
        if T[i].contain(Expression) then
                T[i].remove(Expression)
        end
        if T[i].contain(Punctuation) then
                T[i].remove(Expression)
        end
        if T[i].contain(URLs) then
                T[i].remove(URL)
        end
end
for i = 1 to n_trans do
        T[i].NumWithinDist ← 0;
        for j = 1 to n_trans do
                if ((j ≠i) && (CosineSimilarity(T[i],
T[j]) ≥ r)) then
                        T[i].NumWithinDist + +;
                end
        end
end
Tsorted ← Sort (T, NumWithinDist, ascending);
n_noise ← Ɛ* n_trans;
N ← Tsorted [1...n_noise];
P ← Tsorted [n_noise + 1...n_trans];
return N, P;
```

The above algorithm efficiently removes the noise from the dataset. It scans the complete dataset and removes the html characters, stop words, expressions, URLs and punctuations. It further preprocesses the data through identifying hyperclique patterns with the value of support and h-confidence measures. Both the support and h-confidence measures are specified by the user. This helps to eliminate any objects/items that do not belongs to any hyperclique pattern.

2.2 Machine Learning based Predictive Model (Market Basket ANN)

The second phase of this research is predictive model based on machine learning which is, Artificial Neural Network based predictive model [18]. It predicts the customer buying behavior through following parameters: weight assignments and combinations using associative rules.

2.2.1 Artificial Neural Network

A network sigmoid function is presented which is used to be a function for activation. The neurons in hidden layer are allowed to be in the form of neural networks were detected in features and captured in data patterns. This performs the non-linear mapping between input and also the output variable. Such results are achieved in simulation which predicts to offer the improved and exact results.

Weight calculation:

The products combination is determined by weight calculation algorithm. It is required to calculate the weight of the product. The proposed algorithm converts the product dataset into the Artificial Neural Network (ANN) model. From the Neural Network model, the weight of each product is calculated based on number of edges. The weight is calculated by number of edges that refers the certain node, i.e., product.

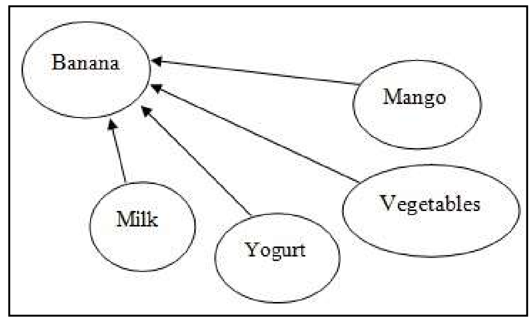

Figure 2: Weight Calculation

The above example illustrates the weight calculation technique from ANN model. Here, the banana contains 4 edges which are referred by mango, vegetables, milk and yogurt. So the weight of banana is 4.

Algorithm 2: Weight calculation algorithm

```
Prod [ ] -> products in the dataset
Edge -> Number of edges which refers the specific Prod [ ]
e [ ]-> single count of edge which refers the specific Prod [ ]
n-> number of products in the dataset
Input: Preprocessed dataset
Output: Weight of each product.
for i=1 to n;
        for each Prod[i]
                Convert to ANN;
        end for
        for each Prod[i]
                Edge=e[i];
        end for;
end for;
return edge;
```

It initially converts datasets into Artificial Neural Network model. Then it calculates the amount of edges refers to the single product node, from that it calculates the weight of each product.

2.2.2 Combination calculation through *Apriori*

Mining for the associations between larger database items is important technique in data mining. An *Apriori* method is the influential method for the mining of itemsets in frequent for the Boolean function. Such itemsets has a minimum support. The *Apriori* itemsets of all subsets must be frequent. A Join operation finds a candidate set of k-item sets that were generated by the itemsets to be joined with itself. This generation of association rules is divided into two steps. First is the minimum support applied to get all the itemsets in frequent and second is to utilize such itemsets and to predict minimum confidence in order to get the rules. The *Apriori* algorithm finds associations among different itemsets. It is referred to Market Basket Analysis. A dataset may contain large amount of items known as transaction. The output for rules in the dataset depends on data constraints.

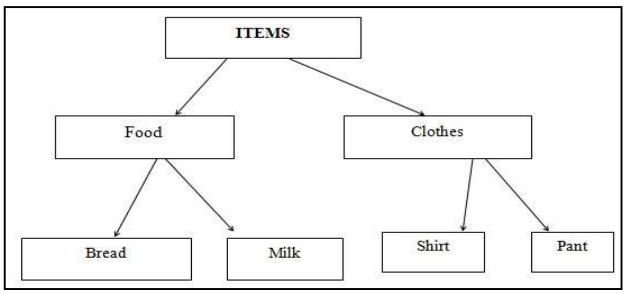

Figure 3: Association Rule

***Apriori* Algorithm**

```
Procedure Apriori (T, minSupport)
{
L1= {frequent items};
for (k= 2; Lk-1 !=∅; k++) {
Ck= candidates generated from Lk-1
for each transaction t in database do
{
 #increment the count of all candidates in Ck that are contained in t
Lk = candidates in Ck with minSupport
 }
 }
return∪;
}
```

The above mentioned *Apriori* is used to obtain the combinations of itemsets.

Support

The rule X=>Y holds with support s if s% of transactions in D contains X U Y. Rules that have s greater than a user specified support is said to have minimum support.

Support of the itemsets is described as proportion of the transactions in datasets having sets of item. The usefulness of the rule is measured with the minimum support. Such parameter measures the quantity of events in an itemset to be matched in both sides of implications in association rules. Such events rules in which itemsets do not matched in both sides are excluded. The itemset which has transaction support as minimum support is determined.

Support = Probability (A and B)

Support = (# of transactions involving A and B) / (total number of transactions).

For example,

Consider ABC is an item.

Total Support=5

Support {AB} =2/5 =40%

Support {BC} =3/5=60%

Support {ABC} =1/5=20%

Confidence

The Rule X=> Y holds with confidence c if c% of the transactions in D that contain X also contain rules that have a c greater than user specified confidence is said to have minimum confidence.

Confidence is termed as a measure of the certainty or the trustworthiness which are associated to each pattern that is discovered. The rule certainty is measured with threshold for the confidence. Such parameters are measured to get the itemsets of events which are matched to left side of implications, and association rules to be matched for right side. Such events rule in which item sets does not matched in the right side are excluded.

Confidence = Probability (B if A) = P(B/A)

Confidence = (# of transactions involving A and B) / (total number of transactions that have A).

Through the support value the proposed technique calculate the association among the products.

For example,

Consider ABC is an item.

Confidence {A=>B} =2/3=66%

Confidence {B=>C} =3/4=75%

Confidence {AB=>C} =1/2=50%

2.3 Optimization based predictive model

The final stage of this research uses the optimization technique to provide accurate and best solution for predictive model.

2.3.1 Similarity calculation:

The similarity function is used to predict the association between the products. The proposed work uses the cosine similarity to obtain the better results. The similarity between the grouped products is measured through:

$$S(A, B) = \frac{A.B}{|A||B|}$$

$|A||B|$ represents the vector distance between the products, which is dissimilarity between the products. It results the better combination of products.

2.3.2 Similarity based Simulated Annealing:
The similarity calculation for each product is taken as the input for this approach. The Simulated Annealing obtains the best similarity values from the input. It provides the optimal solution which found to be highly useful in the Market Basket Analysis.

Simulated Annealing algorithm:

```
Required:
Si (A, B) <- Similarity measure of each products
TSA <- Temporary Simulated Annealing
FSA <- Final Simulated Annealing
i <- 0
j <- 1
for each Si (A, B)
        if (Si(A,B) > Si+1 (A, B)) then
                TSA [i] = Si (A, B)
        else
                TSA [i] = Si+1 (A, B)
        end if
end for
for each TSA [i]
        if (TSA [i] > TSA [i+1]) then
                FSA = TSA [i]
        else
                FSA=TSA [i+1]
        end if
end for
return FSA;
```

Algorithm Description:

The above algorithm describes the exact scenario of the proposed Simulation Annealing model. It takes the list of similarity values as the input and checks each similarity value with its succeeding similarity values. Then the result obtained from this section is stored as the higher similarity value using the variable called TSA [i]. Then each value in the TSA [ ] array is compared with its succeeding TSA [ ] value. It finally obtains the optimal similarity value from the entire values.

3. RESULTS AND DISCUSSION

The experimental results acquired from the proposed technique are described in this section. The research work is carried out through two predictive stages which are described in this section:

3.1 Predictive Model based on Machine Learning
It uses the ANN to calculate the weight of each product in the dataset. The weight calculation is used to obtain the relationship among the variable. The weight calculation of the data is depicted with the sample items as shown in table 1.

Table 1. Weight Calculation

Itemset	Weight
Vegetable	1
Yogurt	6
Ice cream	0
Bags	3
Bread	4
Milk	3
Water	6
Milk	2

From the sample products, the weight of yogurt and water is calculated as 6 which is higher weight than the other products. Milk is purchased 2 times by the customer. So the frequent purchase lists of the given products are easily measurable through this technique.

Then the *Apriori* algorithm is used to compute the combination among the products [17]. The combination is obtained by the use of support and confidence measure. The support is the percentage of transactions which contain both A and B.

Table 2. Support Calculation

Item set	Support
(Bread, Ice-Cream)	100%
(Bags, Yogurt)	63%
(Milk, Water)	67%

The above table depicts the support percentage of itemset. It indicates the percentage of the transaction that contains both the item 1 and the item 2. From table 2, it is observed that the support percentage is high for the product Milk and ice cream. Also the support percentage is very low for the items bags and yogurt.

Confidence is the percentage of transactions that contain B if they contain A. The below depicted confidence values are calculated from the datasets.

Table 3. Confidence Calculation

Itemset	Rules	Prob(antecedent and consequent)/ prob(antecedent)	Confidence
(Bread, Ice-Cream)	If (Bread Then Ice-Cream)	100/100	100%
	If (Ice-Cream And Bread)	100/100	100%

(Bags, Yogurt)	If (Bags Then Yogurt)	63/63	100%
	If (Yogurt And Bags)	63/100	63%
(Milk, Water)	If (Milk Then Water)	67/67	100%
	If (Water And Milk)	67/100	67%

The results shown in table 3 are obtained from the confidence calculation. It is calculated through the rules generated by the associative mining. The rule for the (bread, ice cream) is

Rule 1: If (bread then ice cream)

Rule 2: If (ice cream then bread)

The Rule 1 specifies that the % of customer can buy ice cream when they buy bread. The Rule 2 specifies that the % of customer can buy bread when they buy ice cream. From the generated rule, this technique calculates the confidence value.

The result is further improved by adding similarity function with the datasets. The similarity is calculated through cosine similarity technique. The result obtained from the cosine similarity is depicted in table 4:

Table 4. Cosine similarity Calculation

Itemset	Similarity
(Bread, Ice Cream)	0.98
(Water, Bags)	0.53
(Milk, Water)	0.69

The similarity between the products is calculated by this technique which is used to obtain the better product combination. For example: if two or more products have the confidence value of 100% then the similarity value is utilized to calculate the more accurate product combination. Based upon these results, the Market Basket Analysis is found to be improved [19].

3.2 Predictive model based on Simulation Annealing:

The obtained similarity from each product is provided as the input to the Simulation Annealing technique. The Simulation Annealing is used to find the optimal result from the similarity values. The performance measure of this technique is calculated through the following measures: F-measure, Precision and Recall.

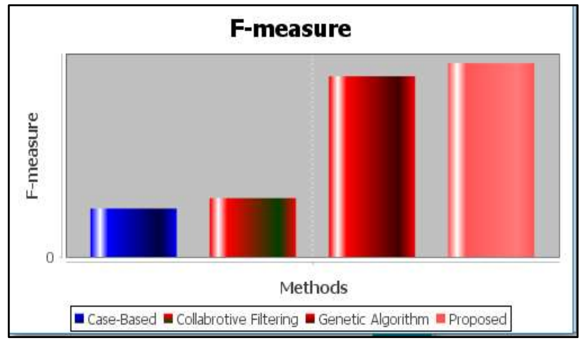

Figure 4: F-Measure

F-Measure is the measure of a test's accuracy and is described as the weighted harmonic mean of the precision and recall of the test. From the above result, it is clear that the proposed technique provides better F-measure value (0.89) than the existing and other kinds of predictive model.

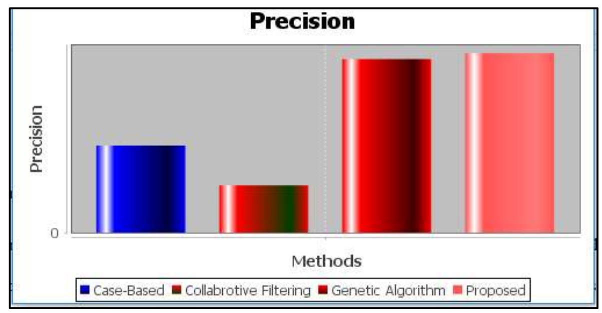

Figure 5: Precision

Precision is described as the amount of relevant instances presents in the retrieved instances. The above figure 5 depicts that the proposed work contains higher precision result (0.92) than the other kinds of existing predictive models.

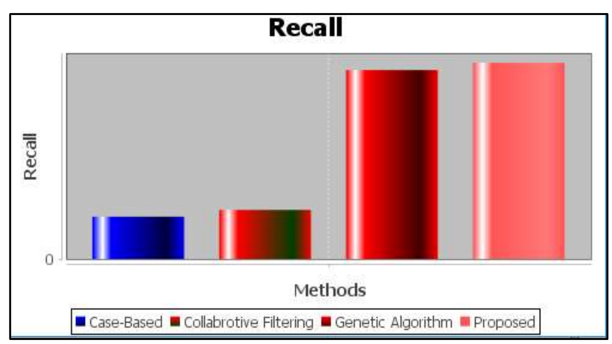

Figure 6: Recall

Recall is described as the quantity of relevant documents which are retrieved successfully. The above figure 6 depicts that the proposed work contains higher recall result range (0.82) than the other kinds of existing predictive models.

4. CONCLUSION

In this paper, we present a novel algorithm for mining customer purchasing patterns. Association rule mining, Artificial Neural Network and Genetic Algorithm is used for that purpose. The system predicts the minimum response time for confidence and support. Noisy data is removed by using Extended HCleaner algorithm. ANN model calculates the weight of the dataset. *Apriori* algorithm used to find the combination of associated products. Then the results are calculated by using Similarity and Simulated Annealing algorithm. The proposed technique introduces a novel method that is Simulated Annealing algorithm in Market Basket Analysis. After evaluation of the proposed algorithm, it is observed that the Simulated Annealing algorithm provides the best and accurate solution.

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