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TiSPHiMME: Time Series Profile Hidden Markov Ensemble in Resolving Item Location on Shelf Placement in Basket Analysis

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ABSTRACT

A market basket in principle, mines/applies a variety of rules that tries to associate a set of items sold together and thus, generate sales transaction data in volumes daily. Its outcome is to provide users with adequate data against the issue of unnecessary item stock-up or inventory stock-out; Thus, averting un-needed demurrage, and provide clients with better decision and improved services. With such itemset (as a basket) seen to be time-bound, client-behavior over time does framework forecast, product that are commonly purchased vis-à-vis the itemset combination called a basket. We must also account for change in the features of a product vis-à-vis a corresponding change in shelve placement of the item – even as consumers change about their selected itemsets combination(s). Thus, our study explores a time-clustering algorithm that exploits (and mines) the Delta Mall (ShopRites) datasets to examine purchase behavior, preferences, and the frequency of itemset combination for each customer. For this model, we generated an average of 162-rules; And the results showed that previous basket items by random customers allow the selection purchase of items of similar value as best combined due to its shelf-placement using the concept of feature drift.

Keywords; TiSPHiMME, Time Series, Hidden Markov Ensemble, Basket Analysis, Internet, Algorithms

1. INTRODUCTION

The inventory demand-supply chain and its management continue to ripple various data that must be collated and processed across many businesses. With much of such data unprocessed, yields various range of complications. This has thus, continued to attract the attention of many researchers. With various heuristics, methods, and models used by researchers, many studies still ensue in a bid to seek better alternatives (Avinadav, 2020; Chenavaz & Pignatel, 2022; Ojugo & Eboka, 2019).

Market basket is a data mining method that identifies products that are purchased at the same time on each transaction. It outputs a set of rules that indicate the products that are purchased at the same time and used in prediction (Saxena & Rajpoot, 2021; Sheen et al., 2021). The rules generated by MBA are association rule(s) of the form: If antecedent (A), then consequent (B). Each rule is equipped with a support level that indicates the number of transactions containing A and B and a confidence level that is a measure of accuracy which is the rule of association rules. Each rule is also equipped with an expected condition and a lift, so that for each antecedent (A) and consequence (B), both the support, confidence, expected confidence, and lift are expressed in (1-4) respectively using Figure 1 (Coscia et al., 2016). If we define $h \subset \{1,2,\ldots,P\}$ and A, B $\subset h$ – so that A U B = h, and A ∩ B = $\varnothing$. Then, we have that (Aghware et al., 2023b, 2023a; Barbu, 2013; Ojugo & Eboka, 2021; Russell & Urban, 2010):

$$P(h) = P(A,B) = \frac{No. of\ Transactions\ A\ \&\ B}{No. of\ Transactions} \quad (1)$$

Equation (1). P(h) is ***prevalence*** or ***support*** and yields how often the combination A and B co-occurs.

$$P(B\,|A) = \frac{P(h)}{P(A)} = \frac{No. of\ Transactions\ A\ \&\ B}{No. of\ Transactions\ A} \quad (2)$$

Equations (2). P(B|A) is ***the confidence*** value that yields the confidence that item B appears in the basket given A is already in the basket. Thus, we use the rule A → B.

$$P(A\mid B) = \frac{P(B)}{P(h)} = \frac{No. of\ Transactions\ B}{Number\ of\ Transactions} \quad (3)$$

Equation (3). P(A)P(B) ***expected confidence*** yields the confidence on how frequently items A and items B co-occur in the number of times that item B is chosen and placed in the basket.

$$Lift = \frac{Confidence}{Expected\ Confidence} \quad (4)$$

Finally, Equation (4). L(A, B) ***lift*** of the rule A → B yields a measure of how much more confident we are in item B given that we see item A in the basket (Ibor et al., 2023; Li et al., 2021; Malasowe et al., 2023; Ojugo & Yoro, 2021a; Oladele et al., 2024; Shroff et al., 2021).

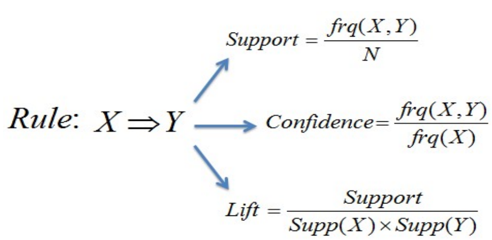

Figure 1. Schematic representation of a rule

2. MATERIALS AND FRAMEWORKS

2.1 Predictive Clustering Approach Using Time Series Dataset

A time series is a set of sequential observations in time that are typical, and dependent. The time series analysis is primarily, concerned with the method of such dependence. The goal of the time series analysis is to model a process that generates the data, provide a compact description, and understand the generating process (Huang et al., 2021; A. Patil & Gupta, 2017; Zhao et al., 2020). To allow for the possibly unpredictable nature of future observations, the selection of a probability model for processing is very important. Albeit, a time series model for observed data {xt} is the specification of the joint distribution of a sequence of random variables {Xt} of which {xt} is postulated to be a realization.

It refers to the use of a model to forecast future values of the series, based on known past values before they are measured (Reyes & Frazier, 2007). A time series consists of many underlying components – some of which, are predictable; and others, random or difficult to predict. Decomposing a series to analyze the behavior of each component – helps to improve the accuracy of its forecast. A variety of time series models can be used such as exponential smoothing, autoregressive integrated moving averages, etc (Kaur & Kang, 2016; Tomar & Manjhvar, 2015). The predictive model seeks to construct systems that predict the target property of an object from the given description of an object (Ojugo & Otakore, 2018b). The models learned apriori from sets of examples denoted as (D, T) – where D is the object's description, and T is the target property value. Clustering conversely, seeks to group objects into subsets of objects (clusters) similar to these descriptions D; But, they have no defined target property (Fatima & Pasha, 2017; Ojugo & Otakore, 2018a). Predictive clustering seeks to combine elements of prediction and clustering. Thus, it seeks clusters of examples similar to each other – having both a description D and target property T parts.

Predictive models are associated with each cluster – as it assigns new instances to clusters based on a description D, yielding a prediction for the target property T. A decision tree (i.e. a predictive clustering tree) is one in which each node represents a cluster. The conjunction of conditions on the path from its root to a node gives each cluster's description. Essentially, each cluster has a symbolic description in form of a rule (IF *conjunction* of conditions THEN cluster), while the tree structure represents the hierarchy of clusters (Eboka & Ojugo, 2020; Ojugo & Eboka, 2018a).

2.2. Market Basket Analysis

Association rule mining (or affinity analysis) is a method commonly employed in retail marketing for market basket analysis. It helps business managers and retailers to easily find and place (side-by-side on the shelf) products that are commonly (and/or seemingly) purchased together to improve sales. These products are often placed thus for eased identification and to enhance cross-selling or combined-selling opportunities, better manage the inventory as well as optimize the store layout (Kaur & Kang, 2016; Ojugo & Yoro, 2021b). By no small feat, association rule mining is the most widely and commonly accepted standard/method for Market Basket Analysis; But, many argue that it is not always the best suitable method for analyzing big market-basket data. When, there is a large volume of sales transactions with a high number of products, phase-off of old items and requisite replacement of new counterpart products, and time-varying demand-supply chain (with the concept of feature drift and feature evolution), the data matrix to be used for association rule mining usually ends up large and sparse, resulting in longer time to process data as well as generation of trivial rules with little insight (Ojugo & Otakore, 2020b; Shiokawa et al., 2016).

MBA is a subset of market research that researchers are now paying special attention to with more detailed [6]. ANN was used to predict inventory stock proving that ANN offers benefits like computational efficiency, more accuracy, and saving time (Chenavaz & Pignatel, 2022). That most models cannot discover important purchase patterns if there are multiple stores. Others converted all market baskets into the maximum-weighted problem to discover the large item patterns (Li et al., 2021). Some studies used an optimization model for shelf-space management problems in which products are grouped into families so that the location of each family was determined using the cataloging method. They considered shelf location effect on sales; But, did not attend the cross-selling effect. Thus, they did not use the purchase data. Another study proposed a method for dealing with shelf-space management problems that consist of two parts. The first phase used a statistical model to measure the impact of shelf layout on sales; the second part used simulated annealing to maximize expected total profit (S. Patil & Saraf, 2015; Shroff et al., 2021).

Another proposed a hierarchical cluster model for retail items, applying the concept of 'distance' between the entities or, groups of entities to achieve the purpose of market-basket analysis (Saxena & Rajpoot, 2021). While using the memetic model-based solution using the deep learning neural network. A total of 56-rules were generated for each solution approach, and the top rules had a fitness range [0.8, 0.865]. 22-out-of-56 rules have a profile for candidate itemset 3 and above so that the rules search for groups of 3 and above itemset. This increases the chances of detecting basket data and also improves the generality of rules, providing the ability for new itemset and corresponding generated rules – to be added to the knowledgebase (Coscia et al., 2016). Conversely, (Avinadav, 2020) used the moving average model for a company with fluctuating demand, proving that the moving average can accommodate rapid changes in data; And is quite suitable for companies with conditions of a high variety of products and raw materials. But, the method is less appropriate when used to predict long-term predictions. In place of extending these fields, other studies include the exponential smoothing model (Ojugo & Eboka, 2018c), Brown method (Zhao et al., 2020), and Box-Jenkins auto-regressive integrated moving average (Ojugo & Otakore, 2020b; Sheen et al., 2021).

2.3. Problem Description

Consider market data logs of items purchased by a customer. Retailers seek to maximize the ***interestingness*** of the product placement and arrangement on shelves. The location of items on shelves prevail that item clustering via trend profile will help retailers maximize the cross-selling effect of items. Studies have also shown that the location of shelves has a great impact on the selling rate of items. So, the preference function of the retailer depends on these parameters: selling benefit, support and confidence of each pair of items, and the selling possibility of each item from shelves. These parameters are thus integrated into the preference function (pf) as shown in Eq. 5 (Reyes & Frazier, 2007; Sheen et al., 2021):

$$pf = \sum_{i=1}^{m-1}\left[\sum_{l=i+1}^{m}\left[C_{il} + C_{li}\sum_{k=1}^{p}[b_i v_{ik} + b_i v_{ik} x_{ik} x_{lk}]\right]\right] \quad (5)$$

m is the number of items, *p* is the number of shelves, C_{il} is the confidence of a rule (item *i* ⟶ item *l*), b_i is the selling benefit of the *i*th item, v_{ik} is the selling possibility of item *i* when placed into *k*th-shelf, and x_{ik} is binary decision variable with a value of 1 if the item *i* is allocated to shelf *k*; Else, value is 0.

But, (Ojugo & Eboka, 2018c) notes that some restrictions limit preference function value such as the capacity limitation (*cl*) of each shelf. This must be considered as a constraint as thus in Eq. (6) where U_k is the capacity of the *k*th-shelf. The second constraint is the association constraint such that support of rule (item *i* ⟶ item *l*) must be greater than the minimum threshold. The goal function and constraints are non-linear functions, and the decision variable is binary. Thus, we are dealing with a rough feasible space that increases the probability of being trapped at the local optimum. Thus, we use the clustering model as an alternative to rule mining (Bahl et al., 2019; Jung et al., 2021).

$$cl = \sum_{i=1}^{m} x_{ik} \leq U_k \text{ with } k = 1,2, \dots P \quad (6)$$

2.4. Dataset Used

This study wishes to discover important purchase patterns of the customer when and where there are multiple stores as well as help optimize itemset on shelf placement and management. We thus use the time-series clustering heuristics to help us ensure: (a) all datasets of items obtained via cross-selling and combination-effect are grouped into families with baskets classified into the weighted problem to help discover the large item patterns, (b) finding a maximization problem ensures that with products grouped into families, location of each family on the shelf is determined via category-based cataloging method. This, will account for the shelf-location effect on sales as well as ensure that the maximal impact of the shelf-space management and layout on sales is exploited, and (c) the profile clustering method will ensure that the cross-selling effect of items is accounted for and will help maximize expected total profit (Khaki et al., 2020; Khaki & Wang, 2019).

Table 1 shows a binary coded market basket dataset of items as co-selected off the various shelves and placed in the basket at the same time. For example, Category 1 for Item 1 has a prevalence of 0.81. This implies that there is an 81% chance that items 1, 2, 6, and 8 are picked from shelf S01 and placed in the basket. The Delta Mall market basket dataset was employed to simulate the model as well as yield cum describe the proposed model-based solution. Thus, the system shows eight items that must be allocated to four shelves. Also, based on the shelves' positions, each shelf has a different impact on the selling possibility of allocated goods, and these possibilities were determined by economists and experts as presented in Table 1.

Table 1. Binary representation of the 4-basket/category values

Items	1	2	3	4	5	6	7	8	9	10	11
Category 1	1	1	0	0	0	1	0	1	0	0	0
Category 2	0	1	0	1	1	0	1	0	1	1	0
Category 3	0	0	1	0	1	0	1	1	0	1	0
Category 4	1	0	1	1	1	0	0	0	1	1	0
Category 5	0	1	0	0	0	1	1	1	0	0	1
Category 6	0	0	1	1	0	1	0	0	0	1	0

(Authors' processing and translation)

2.5. Motivation / Statement of Problem

Despite the numerous benefits offered by previous studies, market basket analysis still faces big challenges, particularly with the concept of drift and feature evolution (Ojugo et al., 2023; Ojugo & Nwankwo, 2021; S. Patil & Saraf, 2015; Saxena & Rajpoot, 2021; Shroff et al., 2021):

1. Classifying transactional data will continue to pose issues to retailers due to the phase-off of old products, the introduction of new products, replacement substitutes, etc. It consequently yields infinite possibilities of cross-selling options; This makes it impractical to store and use historic data for training. A naive solution is to seek itemsets in each basket, store them assiduously and run an algorithm to find the most frequent pairs. These solutions, however, are impractical as many market baskets contain billions of different item pairs (combination). It is plausible to expect that certain pairs are much more popular than others. Thus, the need for a clustering model (Ojugo et al., 2013, 2021a; Ojugo, Aghware, et al., 2015b; Ojugo & Eboka, 2020a).
2. Previous research on transactional data makes stationary assumptions through training cum testing associative rule mining algorithms on observed datasets acquired from the same population. This deprives the model of the needed flexibility to adapt to non-existent data not there from outset, and the robustness required to handle feature evolution and concept drift inherent in transactional dataset streams (Ojugo et al., 2015; Ojugo & Eboka, 2014).
3. Study is necessitated by the increasing need for portable computing and market basket models for such platforms with its major consideration as limited speed and memory of such computing.

Our goal is to use a profile solution to ensure: (a) concept of distance between items are retained, (b) sales quantities of commonly purchased items are positively correlated, (c) with sales quantities of these items observed over different times, what trend series/pattern will be generated and assigned to the same cluster – so that, each cluster contains a set of items analogous to an itemset in association rule mining (Kang et al., 2020; Kaur & Kang, 2016). This in turn, will help to resolve the challenges of feature evolution and concept drift with product location on shelf placement (Lobato, 2018).

2.5. The Experimental Time Series Profile Hidden Markov Ensemble (TiSProHiMME)

The profile HMM as a variant of the fundamental HMM (a) makes explicit use of positional (alignment) data contained in the observations or sequences (Ojugo & Oyemade, 2021), and (b) it allows null transitions, where necessary so that the model can match sequences that include insertion and deletions. Used in basket analysis, O is each transaction rule, T is the time the transaction took place, N is the number of transactions in the (hidden) Markov model, α is the alphabet of the model, and M is the number of symbols in the alphabet, π is the initial state of transactions database,

A is state transition probability matrix, a_{ij} is the probability of a transition from the state *i* to *j*, B contains N-probability distributions for the transactions in the knowledgebase (one transaction per state of the Markov process) (Cao & Guo, 2017; Eboka & Ojugo, 2020; Ojugo & Yoro, 2013; Prey, 2018). Thus, we have that $HMM = (A, B, \pi)$. Note that though, the parameters for HMM details are incomplete as above; But, the general idea is still intact (Meier & Manzerolle, 2019; Ojugo et al., 2014; Ojugo & Eboka, 2020c; Reyes & Frazier, 2007; Saura et al., 2019).

The experimental time series profile hidden Markov ensemble (TiSPHiMME) consists of transaction rules that are aligned as a sequence with significant relations as in Figure 2. The output sequence helps to determine if an unknown transaction is related to a sequence belonging to a class.

We then use the profile, HMM to score transactions and make a decision. Circles are ***delete*** state for unclassified transactions, ***diamonds*** are insert states that allow gaps in transactions upon which the knowledgebase is updated; while, ***rectangles*** are matched states that accurately classifies transaction into class type as in the standard HMM (Ojugo & Eboka, 2019). Match and insert are emission state observations made as PHMM passes via the states. Emission probabilities corresponding to B in an HMM model is computed based on the frequency of symbols (transaction and their amounts) emitted at a particular state (and position-dependent), in contrast to standard HMM. Finally, ***delete*** states allow the model to pass through the gaps, existing in the network to reach other emission states (Avinadav, 2020). These gaps are necessary for the model to help prevent it from over-fitting of data. To calculate probabilities for each possible case, we use the forward algorithm recursively by reusing scores calculated for partial sequences via (7-9) as thus (Ojugo & Eboka, 2019, 2020b):

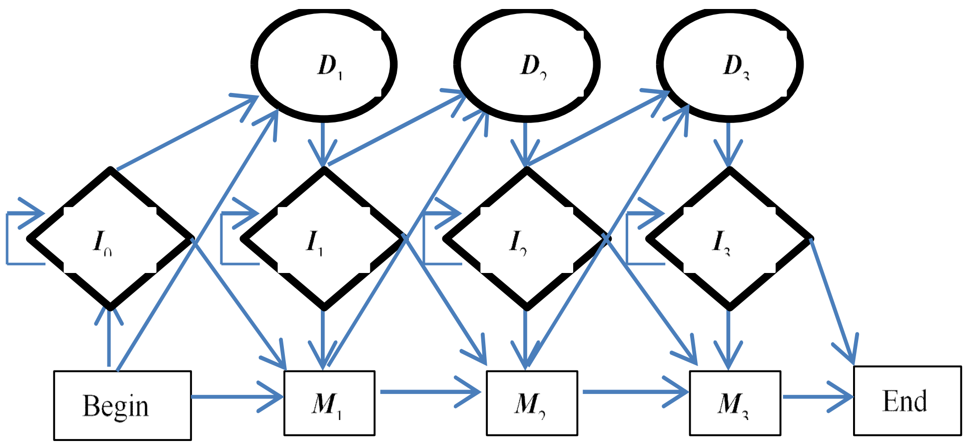

Figure 2. PHMM with 3-match states (Source: (Ojugo, Eboka, et al., 2015a; Ojugo et al., 2021b))

$$F_j^M = Log\frac{eM_j(x_i)}{qx_i} + \log(aM_{j-1}M_j \exp\left(F_{j-1}^M(i-1)\right) + aI_{j-1}M_j \exp\left(F_{j-1}^I(i-1)\right) + aD_{j-1}M_j \exp\left(F_{j-1}^D(i-1)\right) \quad (7)$$

$$F_j^I = Log\frac{eI_j(x_i)}{qx_i} + \log(aM_jI_j \exp\left(F_j^M(i-1)\right) + aI_jI_j \exp\left(F_j^I(i-1)\right) + aD_jI_j \quad (8)$$

$$F_j^D = \log(aM_{j-1}D_j \exp\left(F_{j-1}^M(i)\right) + aI_{j-1}D_j \exp\left(F_{j-1}^I(i)\right) + aD_{j-1}D_j \exp\left(F_{j-1}^D(i)\right) \quad (9)$$

With the large volume of sales transactions and a high number of items combination as well as item phase-off and replacement in the time-varying demand-supply chain, employing the data matrix for association rule mining becomes large and sparse. Thus, it will result in longer processing time and the generation of trivial rules of little insight.

We employed a clustering approach on transaction data formatted as time series – as a superior alternative (to association analysis) for the following reasons (Camargo & Young, 2019; Ojugo, Eboka, et al., 2015b; Okobah & Ojugo, 2018):

1. A data matrix required by association analysis becomes very large when there are many sales transactions and products. Data matrix becomes sparse if each transaction involves the sales of only a few products (Ojugo & Oyemade, 2021; Oyemade & Ojugo, 2020).
2. Conversely, trend clusters are consistent with time series sales transactions that can result in a substantially smaller data set that requires less time to process (Ojugo & Otakore, 2021; Oyemade et al., 2016; Oyemade & Ojugo, 2021).
3. Time series clustering can be used to identify products that are commonly purchased across a certain period. Such patterns are otherwise hard to discover using association rule mining, which analyses transactions without temporal consideration (Allenotor et al., 2015; Allenotor & Ojugo, 2017; Mustofa et al., 2023; Ojugo & Otakore, 2020a; Ojugo & Yoro, 2020).

3. FINDINGS AND RESULT DISCUSSION

3.1. Ensemble Evaluation

Figure 3 shows time convergence for TiSPHiMME against known successful ensembles. It takes an average 6-epochs for the proposed models to yield optimal solution convergence in 16-seconds; while, rule-processor, GA, and GANN yields an approximate 32-epochs with 133seconds, 13-epochs with 102seconds, and 9-epochs 32seconds respectively. It is seen that the experimental TiSPHiMME outperforms the other ensembles. And agrees with (Okonta et al., 2014; Wemembu et al., 2014; Yoro & Ojugo, 2019a, 2019b).

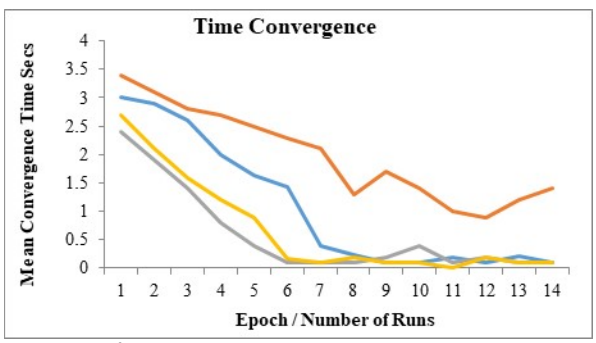

Figure 3. Time convergence on the datasets

3.2. Classification Accuracy and Convergence Time

The issues in concept drift and evolution shift, other major concerns include itemset allocation shelves, shelving arrangement, etc. These attributes to the selling benefit of the various combination of itemsets. In maximizing the expected selling, the itemset with the higher benefits must be allocated to shelves with higher selling possibilities and with a certain shelf placement and arrangement. While table 2 shows that the itemset of Category 1 data family (i.e. C1-1) has an 81% prevalence chance of being purchased alone. It agrees with (Cao & Guo, 2017; Izang et al., 2020; Ojugo & Otakore, 2021). C1-2 implies itemset of Category 1 data-family has a 41% chance of being placed in the common basket etc.

The basket dataset was used to simulate and yield the proposed model-based solution in agreement with showing eleven items that must be allocated into six categories. Studies also reveal that based on shelve positions, each shelf has a varying and different impact on the selling possibility of allocated goods – as determined by economists and experts as presented in Table 1. This agrees with (Coscia et al., 2016; Ojugo & Eboka, 2018b; Ojugo & Ekurume, 2021b, 2021a).

$$\binom{p}{k} = \frac{p!}{k!\,(p-k)!} \equiv \frac{11!}{6!\,(11-6)!} = 462\ cross - selling$$

Table 2. Category cross-selling possibility of item families

C	1	2	3	4	5	6	7	8	9	10	11
1	0.8	0.4	0.1	0.9	0.2	0.2	0.3	0.8	0.7	0.4	0.5
2	0.5	0.2	0.5	0.1	0.9	0.7	0.1	0.2	0.4	0.3	0.2
3	0.3	0.8	0.6	0.2	0.2	0.2	0.1	0.1	0.6	0.2	0.9
4	0.5	0.7	0.1	0.5	0.3	0.4	0.0	0.4	0.5	0.1	0.4
5	0.4	0.1	0.0	0.9	0.1	0.2	0.1	0.2	0.7	0.2	0.8
6	0.5	0.5	0.5	0.0	0.3	0.2	0.7	0.2	0.6	0.4	0.3

Tables 3 and 4 shows the support and confidence simulated values of the itemsets – noting support combination of itemsets that sells better in common, and confidence with which the combo group as a category allows them to be sold. The number of sets of size *k* picked from p items yields. This agrees with (Christopher & Lee, 2004; Izang et al., 2019; Martin-Herran et al., 2006; Ojugo & Eboka, 2019, 2020b; Okonta et al., 2013; Yoro, Aghware, Malasowe, et al., 2023).

Table 3. Support values of dataset item families (S_{il})

Ca	1	2	3	4	5	6	7	8	9	10	11
C1	0.4	0.3	0.1	0.0	0.1	0.2	0.1	0.4	0.9	0.2	0.6
C2	0.0	0.3	0.1	0.1	0.2	0.3	0.1	0.2	0.3	0.3	0.5
C3	0.0	0.0	0.4	0.1	0.2	0.1	0.3	0.3	0.4	0.3	0.4
C4	0.0	0.0	0.0	0.4	0.1	0.0	0.1	0.2	0.7	0.1	0.3
C5	0.0	0.0	0.0	0.0	0.6	0.2	0.2	0.1	0.5	0.2	0.2
C6	0.0	0.0	0.0	0.0	0.0	0.9	0.2	0.2	0.3	0.3	0.1

Table 4. Confidence values of simulated data (C_{il})

	1	2	3	4	5	6	7	8	9
C1	1	0.52	0.43	0.24	0.35	0.49	0.13	0.10	0.27
C2	0.52	1	0.35	0.25	0.63	0.03	0.21	0.30	0.45
C3	0.43	0.33	1	0.20	0.38	0.39	0.13	0.21	0.36
C4	0.23	0.24	0.20	1	0.67	0.32	0.13	0.12	0.12
C5	0.36	0.65	0.39	0.67	1	0.88	0.31	0.26	0.32
C6	0.49	0.01	0.41	0.32	0.87	1	0.11	0.16	0.23
C7	0.11	0.19	0.10	0.12	0.29	0.10	1	0.23	0.43
C8	0.09	0.32	0.19	0.11	0.26	0.16	0.24	1	0.55
C9	0.01	0.21	0.29	0.19	0.32	0.23	0.34	0.54	1

4. CONCLUSION

Our profile trend clustering-based model cum solution used for classification of market basket data yields robust optima in the shortest amount of time for such a dynamic and complex task. The rule helps to yield a better binary combination of data values in the model. The cluster model exploits the Delta Mall dataset to yield optima with appropriate parameter selection that must be encoded via model's structured learning (Acemoglu et al., 2006; Akazue et al., 2022, 2023; Ojugo, Aghware, et al., 2015a, 2015b; Yoro, Aghware, Akazue, et al., 2023). This, helps us to address the issues of profile score criterion for parametric dependencies imposed on the model by stochastic heuristics adopted, and resolve conflicts imposed with dataset encoding. The multi-agent model implies that the agents seek to create their own behavioral rules on the dataset used. Thus, the model requires a profile to artificially or arbitrarily bring back candidate solutions (generated rules) within the boundaries so that itemsets are classified within the limit range.

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