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A Critical Review of Market Basket Analysis on Retail Dataset using Data Mining Techniques

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Abstract. The associations between different products can be interpreted using a data mining technique called Market Basket Analysis (MBA). It contributes a vital role to determine the placement of goods, and the design of business strategies for retailers to attract consumer attraction and hence improve the businesses. The relationship among items can be deduced using association rules (AR) from retail datasets. As customer demand changes rapidly and thereby increasing transactional data. So, there is a need to use deep learning (DL) methods along association rules. Therefore, a review is conducted on MBA using AR and DL methods to mine and predict customer purchase patterns from large retail data sets. The objective of the paper is to assist researchers in the implementation of AR and DL methods while conducting MBA to overcome the challenges of large and frequently changing transactional data.

Keywords: MBA; Deep Learning; Association Rules; Mining Pattern; Retail Dataset.

1. Introduction

Nowadays, the size of data is getting large in various areas like medical, banking and retail. But the whole data is not useful to find customer purchase patterns. So, it is necessary to withdraw useful patterns from an immense volume of data. This procedure of fetching important data is known as Knowledge Data Discovery (KDD). The frequent pattern mining helps the retailers to understand customer buying habits and propose new business strategies.

The data mining techniques used to find interesting patterns are an association, clustering, predictions, classification and outlier analysis (Blattberg et al., 2008). The association rules are used to find significant associations in data sets. In the following example, there are transactional data consisting of transactional ID (TID) and Items as shown in Table 1.

Table 1. Transactional data consisting of transactional ID (TID) and Items

TID	Items
1	Bread, Jam
2	Bread, Egg, Jam, Diaper
3	Bread, Jam, Diaper
4	Bread, Milk, Jam, Coke, Diaper
5	Bread, Milk, Coke, Diaper

Dataset is expanding in volume day by day due to expanding requests of clients. The conventional strategy takes more time to discover obtaining behavior due to the huge volume of items and clients. So, there require profound learning strategies for visit design mining (Grewal et al., 2017).

Example of association rules are:
{Bread} ⟶ {Jam}
Left hand side item known as antecedent and
right-hand item as consequent.
Customer who buys Bread also buy jam.

{Bread, Jam} ⟶ {Diaper}
customer who buys bread and jam also buy Diaper.

2. Significance of Market Basket Analysis

MBA is a significant technique to enhance profit by monitoring consumer buying habits. The most frequently bought products can be bundled to increase sales at a reduced price. In today's competing market MBA can assist retailers to obtain a forefront benefit so four advantages of conducting an MBA are listed below (Berry & Linoff, 2004):

- Finding high-affinity products,
- To improve visual merchandising,
- Optimized assortment of items on online shop,
- To predict upcoming influencing products.

2.1. Finding high-affinity products

Finding interdependence between two purchased products is an efficient way to uplift profit. Analysis of purchasing patterns helps the retailer suggest new promotions. These promotion increases the sale of one item with another purchasing item if buying behavior is known. These associations also help to predict the new category of product for the future needs of the customer. Traditional methods are not sufficient due to the increasing volume of data and customers so this problem can be solved using market basket analysis in a well-organized way.

2.2. To improve visual merchandising

Placement of a product attracts the customer to purchase a product and increases the sale of the product. Retailers are interested to know the in-store placement of products. Store layout affects sales if most purchasing products are placed fastidiously. If most buying product is known and placed on the shelve with another product, then there are chances to increase the sale of that product. It can also be effective to know the store shelve of the new products. Conventional methods are not easy to apply here because of growing market needs. So, market basket analysis is an efficient way to optimize store and product layout.

2.3. Optimized assortment of items on online shop

The layout of products also affects sales of online stores. To know customer cart and visiting patterns helps in online store layout. An efficient product arrangement in the e-store increases sales of the product. It also helps to predict for cross-selling and upselling of products. Market basket analysis is vital to knowing the e-store layout.

2.4. To predict upcoming influencing product

Due to the growing demands of customers retailers are always interested to introduce new products so they can compete in the market with leading businesses. Finding the interest of the customer and predicting future needs is impossible with conventional methods. Market basket analysis is used to predict stockpiling and introduce new features of the product for the future.

3. Critical Structured Literature Review

3.1. MBA using Association Rules

Affiliation rules utilized to mine visit buy conduct of clients that exist in the value-based dataset (Ahmed, 2004). MBA using Apriori and FP-Growth algorithms retail dataset conducted by Chen et al. (2005), Nafari and Shahrabi (2010), Avcilar and Yakut (2014), Zulfikar et al. (2016), Abusida et al. (2019), Nur et al. (2019), Sutisnawati and Reski (2019), Adali and Balaban (2019), Kavitha and Subbaiah (2020), Liansyah and Destiana (2020), Alfiqra and Khasanah (2020), Yudhistyra et al. (2020), Fang et al. (2018), Ariestya et al. (2019), Anggraeni et al. (2019), Rizqi (2019), Mustakim et al. (2018), Hidayat et al. (2019), Hossain et al. (2019), Unvan (2021), and Choi and Yu (2008).

3.1.1. Apriori

Chen et al., (2005) mined client buy designs utilizing Apriori calculation by joining client statistic factors such as Recency, recurrence, and financial (RFM) values with an exchange dataset of food mart over time. Relatively (Nafari & Shahrabi, 2010) worked on shelf arrangement of products for supermarkets located in Iran. The novel work is considering price effects in a shelf arrangement. The experiment shows that Using Apriori-TdMl 102, 329, and 1579 frequent item sets found for categories, subcategories and products respectively at a minimum support of 0.1 and confidence of 0.1. Cross-selling profit for frequently buying products is shown for 6 products. The shelf space is allocated for high cross-selling products at lift 2.75. For future work use Deep learning methods to predict the shelf arrangement of products using a large transactions dataset. While, (Avcilar & Yakut, 2014) worked on the real transactional dataset of the store to mine patterns between in-category and cross-product categories. The experimental results show that the 8 best rules were extracted using Apriori at a minimum support of 0.05% and confidence of 50%. For future work extracting time base association rules and predicting customer Demographic information using deep learning methods. So also, (Zulfikar et al., 2016) connected advertise bushel investigation to discover visit things utilizing Apriori Calculation at eight clusters of XMART retail company in Indonesia. To review critically graphical visualization, add more value to comprehend statistics inefficient way. So, to explore support and confidence in comprehending the way use of a scatter plot is required. Graph-based visualization of association rules is required to explore frequent item sets. Data mining tool to implement Apriori is not mentioned. The performance of the applied algorithm concerning time and memory is not plotted. The persuasive work of the author is an implementation of CRISP-DM to conduct research. A real dataset is used to find frequent patterns.

Comparatively, (Abusida & Gültepe, 2019) planned a trading technique for arranging and buying datasets of power companies applying apriori calculation. The affiliation rules produced at tall certainty esteem of 100% appearing visit request save parts. Furthermore, (Nur et al., 2019) mined frequent item sets for Fonzu Premium restaurant using the apriori algorithm and built-in system. At confidence 100% If a customer ordered Gyoza Saikoro Yakimeshi and then would order Chicken Teriyaki Don. Results are then verified using built-in systems. Simulation of association rules is shown comprehensively. Graph-based visualization of association rules is not shown properly. Plotting of support and confidence is required to visualize stats using a scatter plot. Likewise, (Sutisnawati & Reski, 2019) applied the apriori algorithm to transactional data of XYZ Restaurants to find purchasing patterns of customers. At confidence 65% 2 pairs of products Nasi-Bakso Ikan purchased frequently. Simulation of applied apriori algorithm is shown comprehensively. A data mining system is designed to analyze data efficiently. To review critically interface of the designed system is not attractive. A visualization interface is required for association rules, support and confidence using graph base and scatter plot. While, (Adalı & Balaban, 2019) developed a dynamic model to mine frequent patterns of X-firm in the electricity sector. A dynamic model can be used to generate rules during any year with dynamic values of support and confidence. The dynamic model is developed using the Apriori algorithm. A Scatter plot of rules is used to examine frequent items. A business strategy for X-Firm is proposed on the obtained results. The interface of the model can be used without any technical knowledge to make business decisions on a dataset in the future. To review critically dynamic model with other ARM algorithms can be implemented for better analysis of customer buying behavior.

Kavitha & Subbaiah, (2020) implemented an apriori algorithm on the grocery's dataset to mine frequent item sets. Association rules are generated using a rules package in R. Graph-based visualization of association rules is displayed using the rules viz package. The most buying products are yogurt and butter at the support of 0.007 and confidence of 0.6. The research scope is limited because a built-in dataset is used to mine frequent item sets. On the other hand, (Liansyah & Destiana, 2020) worked on the sales dataset of Lotteria Cibubur restaurant to suggest a business strategy. A data mining application Tanagra 1.4 is used to generate association rules using the apriori algorithm. The most buying products are Hot/Ice coffee and float at minimum support 16% and confidence 100%. In the Data visualization phase graph base visualization is not shown of association rules. A large dataset is required to check the reliability of the apriori algorithm. Comparatively (Alfiqra & Khasanah, 2020) developed business strategy for Supermarket X in Yogyakarta.

Using Apriori association rules are generated for each transaction in four periods. The customer purchasing behavior is fluctuating in every period so OCVR implemented to mine frequent rules. Visualization of frequent itemset and association rules using scatter plots and graph-based visualization is required. At 1%<OCVR<30% generated 17 rules are used for bundling and planogram of frequently buying products. While (Yudhistyra et al., 2020) implemented Apriori and CARMA on Big data to design the business strategy of the metal trading company in Indonesia. A standard process CRISP-DM is followed to conduct research. The web graph method is used to visualize association rules. Results are mentioned with the value of confidence and support with frequently generated rules. To review critically there is a need to develop a flexible real-time model so in the future a new business strategy can be designed using the new model in different periods. Similarly, (Rachmatika & Harefa, 2020) analyzed a small sales transaction dataset using the Apriori algorithm to propose a business strategy. To review critically standard process not followed, visualization of itemset and association rule not shown, to conclude results business strategy not defined properly. Similarly, (Fang et al, 2018) proposed dynamic product bundling using Association rules and clustering algorithms. The novel work is dynamic product bundling to save time and energy for customers. The result shows that at a minimum support of 0.1 and confidence of 0.01 three rules were generated using Apriori to find necessary products for bundling. Four clusters of Customers using K-means identified on values of R, F and M to recommend product bundles. The summary table of MBA implementing Apriori is shown in Table 2.

Table 2. Summary Table of MBA using Apriori algorithm

Author Year	MBA using AR	Preprocessing	Dataset	Result	Improvement	Good
Chen et al. (2005)	Association rules with apriori algorithm	Data transformation , integration and segmentation	Transaction data of food Mart including customer, product and transaction database	At minimum support and confidence of 20% generated 111 and 78 rules for first and second periods respectively	Visualizations of results Use of large real transactional dataset	developed an online system to mine customer patterns at different time
Safari and Shahrabi (2010	Association rules using Apriori- TdMl	Not mentioned	Retail dataset of supermarket in Iran of four months with 1241 products 7305 sales transaction.	Using Apriori-TdMl 102, 329, and 1579 frequent item sets were found for categories, subcategories and products respectively at	Deep learning models to predict shelf arrangement of products. Use of large transactions dataset.	Product shelf arrangement considering the price, product cross-category purchase and temporal effects.

				a minimum support of 0.1 and confidence of 0.1. Cross-selling profit effect for frequently buying products. At lift 2.75 shelf space is allocated for high-selling products		
Avcilar and Yakut (2014)	Apriori Algorithm	Calculated Descriptive statistics of data with Mean, Median, Mode, Maximum & Minimum values. Sales & frequency of products	Sales transaction dataset of the store in Turkey with 9.000 products of 35 categories and 42.390 transaction records from 01.01.2012 and 31.12.2012	At minimum support of 0,05% and confidence 50% extracted 8 best rules	Time base mining of association rules. Predicting customer Demographic information using deep learning methods.	Web graphic view to show association among products Association rules defined clearly
Zulfikar et al. (2016)	Apriori Algorithm	Combining different products on Frequency	XMART Retail in Indonesia 25 products 145.548 record	Generated frequent 10 rules at a minimum support of 12% and confidence of 60% for 8 clusters of stores	Considering sale's day and hour effects on sales	Followed standard process CRISP-DM. Worked on Real Dataset
Abusida et al. (2019)	Apriori Algorithm	Data selection, Data splitting, Data filtering, and Data Transformation to ARFF format.	General electricity company of Libya (GECOL) Dataset properties order number	At confidence 100% 10 best rules are generated for each site	Data visualization of association rules Scatter plot for confidence and support values	Simulation of results
Nur et al. (2019)	Apriori Algorithm	Binarization	Sales transaction data of Fonzu Premium restaurant of month June 2018	With manual calculation at confidence 100% Chicken Teriyaki Don and Gyoza Saikoro Yakimeshi With built-in system calculation at confidence 100% Chicken Teriyaki Don and Gyoza Saikoro Yakimeshi	Considering Seasonal and holidays effects on sales of food	Results are mentioned Simulation of association rules shown Defined research methodology clearly
Sutisnawati and Reski (2019)	Apriori Algorithm	Removed unnecessary Attributes Date, Price, Amount, Total, Location.	XYZ dataset with 157 transactions and 32 items with smallest frequency 2 and largest frequency 68	At minimum confidence, 65% and support 23% 2 pairs are often purchased	Considering Seasonal and holidays effects on sales of food Use of large transaction dataset	Comprehensive Simulation of Results Dynamic analysis of association rules using the developed application
Adali and Balaban (2019)	Apriori Algorithms	missing values, Outlier Analysis, Duplicated Observations, Binarization	Dataset1 from January 2014 to December 2014 with 19 attributes 177393 transaction Dataset2 (2015) with 23 attributes183401 transaction	At support of 0.1% and leverage 185.0291 products, HESNYA-03 & HESNYA-02 in different color packages can be used for promotions	More than one dynamic model can be added by applying different algorithms	Followed CRISP-DM methodology Dynamic model for rules independent of time and region Association rules can be downloaded for analysis
Kavitha and Subbaiah (2020)	Association rules with matrix incidence	Data Cleaning, Data Aggregating, Deleted duplicate data for each transaction	Surabaya restaurant sales with 15087 records from March 23 to June 30, 2018, and September 23 to October 16, 2018 May 17 until June 16, 2018	At minimum support and confidence of 4% and 15% 10 rules	Use of Dimension reduction or feature selection method on a dataset	Data visualization using Power BI Business strategy discussed briefly Research method and flow defined clearly Results mentioned properly Dashboard for making business strategies in the different period

						Data analysis using matrix incidence Considering transaction day week, month and food type on customer purchase
Liansyah and Destiana (2020)	Association rules using apriori	Not mentioned	Dataset from period 2 February 2019	At minimum support, 15% extracted 12 best association rules	Dataset not mentioned with dimensions Considering Seasonal effects on purchase of clothes	Results are not mentioned briefly with Support and confidence
Alfiqra and Khasanah (2020	Apriori Algorithm	Not mentioned	Groceries Dataset 9835 transactions and 169 items.	At support of 0.007, the confidence of 0.6 butter and yogurt most frequent item	Limited Research scope	Visualization of association rules Use of scatter plot to show support, confidence and lift values
Yudhistyra et al. (2020)	Apriori, CARMA	Measuring central tendency, removing null tuples, sorting hashing, Exploring Aggregating and visualizing the relationship. Dataset transformed to 80 variables	3,986,872 observations from 248,856 customers	Apriori: At minimum support of 1% and confidence of 50% 21 rules CARMA: At minimum support of 1% and confidence of 50% 5 rules	A flexible model for development of new model to propose business strategy in different period	Web graph visualization of item sets with weak, medium and strong link Worked on real dataset performance plot of two algorithms
Fang et al. (2018)	Apriori algorithm	Data cleaning, Data reduction, Data integration	Supermarket X dataset of 57784 transactions in a month including 41248 items	At 1%<OCVR<30% generated 17 rules	Scatter plotting of confidence and support. Graphical visualization of association rules	Followed standard research methodology Results mentioned Proposed Business strategy
Ariestya et al. (2019)	Association rule using Apriori Algorithm, K-means clustering finds customer segment using RFM values	Integration data from four database customer, Transaction, products and products classed. Z-score normalization	Electronic Sales Transaction dataset with10281 customers, 251396 records, 1560 products and 110 product categories.	At minimum support 0.1 and confidence 0.01 three rules were generated using Apriori to find necessary products for bundling. 4 clusters of Customers using K-means identified on values of RFM.	Proposing price bundling method by using customer attribute and demands.	Dynamic product bundling to save both time and energy of customer

3.1.2. FP-Growth

While (Ariestya et al., 2019) mined frequent patterns to propose marketing schemes for small grocery stores. ARM, FP-Growth and Apriori algorithms are implemented on a dataset of 602 transactions. To review critically dataset is not mentioned with proper dimensions and source. Performance comparison of applied algorithms not shown. Results are mentioned with support and confidence clearly to propose a new marketing strategy. Anggraeni et al., (2019) worked on a sales dataset of an electronic company in Indonesia. FP-Growth and Apriori implemented using Weka to find frequent item sets for sale promotions. The final results are shown using the Apriori algorithm with support and confidence. The best rules generated by FP- Growth are not mentioned in the results section. Visualization of rules, support and confidence using scatter plot and graph base visualizations are not used. Comparatively (Rizqi, 2019) worked on the product bundling strategy of Retail Z in Indonesia. The research methodology is defined briefly. Dataset of 5 departments with 58 products is used to mine frequent items using FP-Growth. Association rules with confidence, support and lift are mentioned properly. Results are mentioned clearly to bundle products for Retail Z. To review critically Visualization of support, confidence and association rules are required using scatter and graph-based plotting.

A study (Mustakim et al., 2018) observed the most interesting pattern of Berka Mart applying Apriori and FP growth. To review critically Comparison of both algorithms in terms of memory should be plotted to examine performance. To critically analyze values of support and confidence scatter plotting is essential. Graph-based representation of association rules enhanced the understanding of frequent item sets in the finding of patterns. So, graph-based visualization of association rules is required to implement. A comparison of the two algorithms shows FP takes less time in the generation of the rule than Apriori. FP growth scans the database two times to generate frequent items. A standard method is followed and shown pictorially to find patterns. Findings are mentioned with the most frequent rule at specific support and confidence.

Hidayat et al., (2019) describe the application and evaluation analysis of the Apriori and FP-growth algorithm for the Market Basket analysis of brilliant shop. Regarding this article, the authors do not mention which methodology was used for data understanding and pre-processing and also do not describe which tool was used for the results. Authors directly put results in tables rather than showing them in diagrams or graphs and in the results of both algorithms processing time is not mentioned because authors in this research show that the Apriori algorithm takes time enough its scan the database many times but in FP-growth algorithm, it just takes less time and only scan database two times to generate frequent item set. Maliha et al., (2019) in this study used market basket analysis with Association rules and two algorithms respectively Apriori and FP-growth. Researchers used two datasets obtained from Kaggle website 1: French Retail Store 2: transaction of bakery items processed this data by using python tool. In the end, FP- growth and Apriori algorithm comparison regarding time shows in good form. But still needs some improvement on this to improve the accuracy of the algorithm and need to apply it to different transaction datasets to determine the percentage for product reduction. (€Unvan, 2020) in this research doing market basket analysis with Association rules and applying two algorithms Apriori and FP-growth. The researcher used the sales data of any supermarket received from the Vancouver Island University website and processed this data by using Weka tool and finding patterns. In this article results not shown in table forms or graphics need to be shown. The summary table of MBA using FP-Growth is shown in Table 3.

Table 3. Summary table of MBA using FP-Growth

Author Year	MBA using AR	Preprocessing	Dataset	Result	Improvement	Good
Anggraeni et al. (2019)	FP-Growth, Apriori Algorithms	Data cleaning from 620 to 577 data, Data integration, Data selection, Data Transformation	Dataset of 620 items	FP-Growth: At minimum support of 45% and confidence 60% 5 rules Apriori: At minimum support 45% and confidence 60% 3 rules	Dataset with proper dimensions Performance plot of two algorithms Use of the large dataset	Followed standard Research Methodology Results mentioned with support and confidence
Rizqi (2019)	Apriori, FP-Growth Algorithms	Not mentioned	Electronic Sales data from January 2016 to December 2016 116 transactions	Using Apriori at a minimum support of 9% and confidence of 40% 10 best rules	Association rules with FP-growth not mentioned properly Performance plot of two algorithms	Use of the real dataset

			containing 14 items		Visualization of association rules Use of the large dataset	
Mustakim et al. (2018)	FP-Growth	Data cleaning, recapitulating data, removing duplicate data, checking inconsistent data, Data Transformation, cleaning of noise and missing data	Retail Z dataset of 5 Departments with 58 transactions	At minimum support of 30% and 60% generated 6 rules.	Scatter plotting of confidence and support. Graphical visualization of association rules Use of Large dataset Considering price attribute for product bundling	Problem statement mentioned Results with support and confidence Research methodology defined Worked on the real dataset Proposed business strategy on mined frequent patterns
Hidayat et al. (2019)	FP Growth, Apriori	Not mentioned	Berkah Mart Dataset 8,307 items 400 transactions at a day in 2017 October, November, December	Apriori: Frequent itemset found at support 13.02 and confidence 48.37. FP Growth: Frequent item set found at support 13.11 and confidence 48.42	Use of scatter plot for graphical visualization of support and confidence. Graphical visualization of Association rules. Pruning of dataset. Comparison of the algorithm in terms of memory	Comparison of two applied techniques in terms of memory and speed. Use of real dataset. Frequent patterns were mentioned with support and confidence in the result. Standard process followed to mine patterns
Hossain et al. (2019)	FP Growth, Apriori	Not mentioned	sales transaction data of cosmetics in Brilliant Store during November 2018	support value of 8.8% and 30% confidence value, with a filtering time of 0.036 seconds	This research does not show data exploration and does not explain which tool is used to mine the dataset	A good thing in this article is authors used the original dataset to find frequent item sets and patterns.
Unvan (2021)	FP Growth, Apriori	Not mentioned	Two datasets obtained from Kaggle 1: French Retail Store 2: transaction of bakery items	Minimum support=1% and Minimum confidence =50%,	Need to apply to different transaction datasets to determine the percentage of product reduction	FP-growth and Apriori algorithm comparison regarding time shows good form
Choi and Yu (2008)	FP Growth, Apriori	Not mentioned	The sales data of any supermarket is received from the Vancouver Island University website.	21.06 Conviction and 1 (100%) confidence values	Results not shown in table forms or graphics	Good thing authors well describe the association

3.2. MBA using Deep Learning

Deep learning utilized to mine visit buy conduct of clients that covered up in retail dataset (Ahmed, 2004). Market basket analysis using NN and LSTM algorithms on retail dataset conducted by:

3.2.1. Neural Networks

Whereas (Choi & Yu,2008) proposed deals estimating show for mold retail utilizing Developmental Neural Arrange (ENN). The proposed approach outflanks SARIMA show when variances of season impact mold retail. Future attributes of product size and color can be considered to forecast sales more accurately. Essentially, (Chen et al, 2010) proposed determining deals demonstrate utilizing Standard day and occasion moving normal strategy and back engendering neural arrange. The test performed on deals dataset of new nourishment deals at store appears that BPNN outflanks with less MSE and tall accuracy. For future work deals estimating can be done by taking into number the impact of occasions, summer excursions, modern years and autonomy day. So also, (Wang et al, 2016) proposed a multi errand multi-course forecast show for the general store Retail dataset in China. The novel work is the forecast of multi errand and multi-course statistic properties of the client on buying conduct. The pack of thing representation is utilized to discover the visit itemset. The proposed demonstrate Organized Neural Implanting (SNE) performs best utilizing normal amassing pooling work with tall Exactness 0.371, Audit 0.289, F1 0.324 Hamming Misfortune 0.411 and for energetic clients with tall Exactness 0.361, Survey 0.299, F1 0.327 Hamming Misfortune 0.410 and dynamic clients with tall Accuracy 0.361, Review 0.299, F1 0.327 Hamming Loss 0.410. For future work Testing Model efficiency using more datasets with large transactions considering Seasonal and time stamp effects on purchase of items, integrating association rules to find frequent itemset with Deep learning methods. Using deep neural architecture than shallow and Prediction of more demographic attributes to measure the efficiency of the proposed model. Comparatively (Salehinejad & Rahnamayan, 2016) predicted customer shopping patterns utilizing Repetitive Neural Arrange. The novel work is desire of Recency, Repeat and Cash related (RFM) values utilizing RNN to anticipate client shopping plans. The auto- encoding procedure is utilized to remove highlights of input variables Client ID, R, F and M. The proposed illustrate RNN-ReLU outflanks than LSTM-RNN and SRNN to predict RFM values with 80%. Future work can be conducted to use location and age variables for feature extraction. The next item recommendation system can be proposed using predicted RFM values.

Likewise, (Massaro et al, 2018) worked on Walmart's 45 stores sales dataset to predict sales using an Artificial Neural Network (ANN). The preprocessing step is performed using different Operators in Rapidminer. The Profound learning with ANN beats as best deals anticipating calculation with Relationship 73% / 97,4%, Normal Outright Blunder 2000 +/- 1250 and Relative Normal Blunder 12,9% +/- 9,9% than other strategies Slope Boosted Trees, SVM, KNN, Choice Trees and Irregular Woodland. To review critically the following improvement required proposing a Hybrid model using Association Rules and Deep learning to predict sales, use of other deep learning methods LSTM and CNN, and use of dimension reduction algorithm. The persuasive work of the author is the use of a real sales dataset and graphical performance plot comparison of deep learning with other strategies Angle Boosted Trees, SVM, KNN, Choice Trees, and Irregular Woodland. (Lismont et al, 2018) proposed demonstrate to foresee fewer buying items utilizing Client- Item organize as preprocessing strategy. The half-breed Irregular Timberland predicts fewer buying items with tall AUC than neural organize.

Kim et al, (2002) proposed deals forecast show utilizing hereditary based classification of neural systems on deals dataset. The Integration comes almost from three neural frameworks NN1, NN2, and NN3 into a single GA-based procedure that shows up to figure target thing purchase with a classification rate of 76.5% and a botch rate of 13.5. For future work, classification can be extended to abstract and rank levels. So too, (Pale et al, 2015) proposed a novel neural organize approach NN-Rec to foresee the following bushel proposal of two Honest to goodness Retail datasets Tafeng and Beirne. The proposed framework contains three layers embedding, hidden, and output layers. The user id and items id's transformed into the matrix to form a feature vector. The feature vector feed into the embedding layer. The hidden layer transforms h1 to h2 using the activation function. The SoftMax operator is applied at the output layer to predict the probability of the next purchased item. This demonstrates captures long conditions and input layer more adaptable to include other highlights than previous methods. Experiment for Beiren dataset appears precision is underneath 0.1 when wicker container k= 2 and for Tafeng dataset precision is underneath 0.06 when wicker container k=2 using NN-Rec novel neural network approach. Likewise, (Yu et al, 2016) proposed a novel show named Energetic Repetitive Wicker Container Show (DREAM), based on RNN.

The novel work is thought of dynamic user's interest and global intuition of all wicker containers of the client over time. The Max and Avg pooling operation are performed on items in the basket to get basket representation. These basket representations feed as input into the input layer. Energetic representations of the client get in the covered layer. The yield layer appears with scores of clients for all items. The result appears nonlinear operation max-pooling outflanks than Avg pooling strategy since it measures the intuitively relationship of wicker container things. Gangurde et al., (2017) a proposed a novel predictive model for MBA by using data cleaning and a neural network approach. To find frequent item sets for seasonal dataset MBA algorithm takes more time and repeated scans of the database. So, this may be accomplished by changing the weights through backpropagation. This strategy makes a difference minimize the time and taken a toll of performing as often as possible MBA on an expansive database. A handmade dataset was used to simulate the proposed method. Valid four combinations are generated using a threshold of 0 and 1 in the handmade dataset. The proposed framework is implemented on the transaction dataset of online shopping. Analysis of proposed framework with other MBA methods evaluated using metrics of precision, recall and accuracy. Results from the online shopping dataset achieved an accuracy of 0.90. To review critically the source of the dataset and data visualization not mentioned. While (Li et al, 2018) designed an engine to combine current and past transactions to dynamically predict preference for the next item for making real-time business strategies. The obtaining data of clients extricated utilizing Individual Acquiring Inclination Design (PPPP). The Repetitive Neural Arrange (RNN) is connected to the extraction data of PPPP to discover another obtaining thing of the client. Top 100 orders taken as input for each customer. For training data, 97 orders and the remaining 3 orders are considered as testing data. The result shows that PPPP achieves 18.29% higher Individual Prediction Accuracy than Baseline (Apriori). To review critically simulation of the proposed method and prediction results are not shown using RNN on the transactional dataset. The persuasive work of the author is to propose an engine for making real-time business strategies using RNN. The performance of PPPP is shown with metrics.

Comparatively, (Wang et al,2018) proposed an attention-based proposition appear utilizing a neural organize approach. The novelty of work is recommending novel items other than rigid order assumptions using attention base recommendations. ATEM comprises three layers input layer, the thing implanting layer, the Consideration Layer, the setting inserting layer, and the yield layer. The execution of ATEM was assessed utilizing two genuine deals value-based datasets of Insights IJCAI-15 and Ta-Fang. The ATEM performs at REC@10 0.3542, REC@50 0.5134, and MRR 0.2041 on the IJCAI-15 dataset. The ATEM performs at REC@10 0.1089, REC@50 0.2016, and MRR 0.0347. Whereas (Yu et al, 2016) proposed a novel demonstration named Energetic Repetitive Bushel Show (DREAM), based on Repetitive Neural Arrange (RNN). The novel work is thought of energetic user's intrigued and worldwide intuitive of all bushel of the client over the time. The Max and Avg pooling operation are performed on things in the bushel to induce bushel representation. These basket representations feed as input into the input layer.

Energetic representations of the client are gotten within the covered-up layer. On the other hand, (Sreenivasa & Nirmala, 2019) proposed half breed appear to mine client buying conduct on a retail dataset of the T-Mall online shopping store. The novel work is considering zone base information of the client and utilizes lively brief- and long-term consider of the client. To achieve brief-term purposeful move networks are utilized from past exchanges of clients. The hybrid model is designed using RNN and FNN to attain the short- and long-term behavior of customers. The proposed model outperforms other hybrid models with HR 0.08547365 and MRR 0.12935566. In future work, the model can be evaluated using the Amazon dataset with high HR, and MRR values and considering the time-centric information of the customer.

Comparatively, (Lee et al, 2020) proposed a multi-period proposal show utilizing RNN. The system is assessed by different periods since the client obtains conduct changes over time but the conventional proposal demonstrates assessed as it were once. An experiment was performed on a Real dataset of a Fresh Food delivery company with 7716 customers and 10 shopping carts. The result shows that LSTM based recommendation model outperforms the collaborative filtering-based model with an accuracy of 21% high at T and 10% high at T+4. To review critically the use of diverse transactional datasets and propose a hybrid model using CF and RNN-based recommendation models required as improvement in current work.

Changchien et al. (2001) proposed an online suggestion system for electronic stores utilizing clustering and running the appear extraction module. The SOM neural arrange-based plan utilized to find 9 clusters from O-ID, Buyer, Recipient, Item table, and 99 affiliation rules are extricated at least certainty 0.25. For future work proposed approach can be applied to sales and product datasets considering Seasonal effects. The summary table of MBA applying NN is depicted in Table 4.

Table 4. Summary table of MBA using NN

Author Year	MBA using AR	Preprocessing	Dataset	Result	Improvement	Good
Chen et al. (2010)	Evolutionary Neural Network	Not mentioned	Sales data for two fashion products T-shirts and Jeans from 2002 to 2003	ENN outperforms SARIMA when seasonal trend fluctuates in fashion retail	Taking into count the attribute of products color and size	An experiment performed on the real dataset
Wang et al. (2016)	Back Propagation Neural Networks (BPNN) And Logistic Regression (LR)	Not mentioned	35 days of fresh food sales at Hi-Life convenience stores. Fresh foods herein are comprised of four kinds of sandwiches, three kinds of hand-made rolls, two kinds of rice balls, sushi.	The BPNN outperforms with smaller MSE and high precision to forecast sale	Demand forecasting takes into count the holidays, summer vacation, new year and Independence Day	Plotting Sale predictions applying BPNN
Salehinejad and Rahnamayan (2016)	Structured Neural Embedding (SNE)	Filtered dataset with the user who has five demographic attributes. Extracted transaction history of users and removed the items bought less than five times	BeiRen retail dataset of supermarkets in China from 2012 to 2013 with 49, 290, 149 transactions, 220, 828 items and 1, 206, 379 users.	The proposed illustrates SNE performs best utilizing ordinary storing up pooling work with tall Precision 0.350, Audit 0.281, F1 0.312 and Hamming Misfortune 0.431 for Torpid clients. For medium clients with tall Accuracy 0.371, Audit 0.289, F1 0.324 and Hamming Misfortune 0.411. For energetic clients with tall Exactness 0.361, Review 0.299, F1 0.327 and Hamming Hardship 0.410.	Using deep neural architecture than shallow to predict demographic attributes from purchase history. Prediction of more demographic attributes to measure the efficiency of the proposed model Integrating Association rules to find frequent itemset with the deep learning method.	Correlation between demographic attributes. Incorporating Multi-task and multi-class prediction problems. Turning Multiple prediction tasks into a single structured prediction task.
Massaro et al. (2018)	Recurrent Neural Network (RNN)	Splitting the dataset into 50% training,	Ta-Feng grocery shop transaction sales dataset with 817,741	The ReLU-RNN predicts R, F and M values by 80% more	Conducting Experiment on Large Training	Customer behavior

		25% validation and 25% testing.	transactions 32,266 users and 23,812 items.	than LSTM-RNN and SRNN.	dataset. Using location and age variables for feature extraction. Proposing a recommendation system using predicted RFM	prediction using RFM values.
Lismont et al. (2018)	Artificial Neural Network (ANN)	Using "Join" operator to make single dataset, Nominal to Binominal conversion, Split data into training and testing	Walmart 45 store sales forecasting dataset 140000 sales records for each store features.csv scores.csv train.csv test.csv	Profound learning with ANN outperforms as best sales predicting calculation with Correlation 73% / 97,4%, Normal Absolute Error 2000 +/- 1250 and Relative Normal Mistake 12,9% +/- 9,9% than other methods Gradient Boosted Trees, SVM, k-NN, Decision Trees and Random Woodland	Hybrid model to predict sales using AR and Deep Learning. Use of Dimension reduction algorithm on dataset. Applying LSTM OR CNN to predict sales with more high correlation and less absolute and relative Errors.	Worked on Real sales dataset. Comparison of Deep Learning with other methods. Graphical performance comparison plot of applied method ANN with other algorithms Gradient Boosted Trees, SVM, k-NN, Decision Trees and Random Forest.
Kim et al. (2002)	Customer product network for extracting features, predicting less sold product using classification method Random Forest, Decision tree, Logistic regression, Neural network	Customer-Product network used to extract feature of product and customer	European Grocery shop transactional dataset with 6355 products, 406,678 customers ,100 million transactions during the period of 12 months	Random forest outperforms with average values of AUC using local features 0.6616, Network features 0.6902 and Hybrid features 0.6989. The hybrid Random Timberland predicts fewer buying items with high AUC esteem.	Considering long period effects on customer buying behavior and seasonal effects on product purchase. Conducting current research on online dataset of retail. In local feature considering price and promotion other than RFM values.	First customer product network-based study on offline retail dataset.
Wan et al. (2015)	Genetic based classification of neural networks	Not mentioned	Sales dataset of EC company in Korea. Data set consists of 10 demographic features, 5 transactional feature during one year.	Integration of comes about from three neural networks NN1, NN2, and NN3 into Single GA-based method show expectation of target product buy with classification rate 76.5% and error rate 13.5	Applying rank and abstract level classifiers	Experiment performed on two datasets
Salehinejad and Rahnamayan (2016)	Dynamic Recurrent basket Model (DREAM), based on Recurrent Neural Network (RNN)	Dataset preprocessed for each item purchased by at least k users. For Ta-Feng k=10 and For T-mall k=3	Ta-Feng: 817,741transactions belonging to 32,266 users and 23,812 items. T-mall: 4,298 transactions of 884 users and 9,531 brands	Using Avg-Pooling: For Ta-Feng dataset with dimensions {50, 100, 150} f1-Score 0.061 NDCG 0.082, f1-score 0.064 NDCG 0.081, f1-score 0.067 NDCG 0.083 respectively. For T-mall dataset with dimensions {10, 15, 20} f1-Score 0.058 NDCG 0.141, f1-score 0.063 NDCG 0.154, f1-	Heterogeneity of Basket Recommendation Problem. Effects of season and time on datasets.	Use of linear and nonlinear pooling methods for basket representation Performance plot of applied methods with metrics on two datasets

				score 0.066 NDCG 0.160 respectively. **Using Max Pooling:** For Ta-Feng dataset with dimensions {50, 100, 150} f1-Score 0.065 NDCG 0.084, f1-score 0.068 NDCG 0.085, f1-score 0.070 NDCG 0.086 respectively. For T-mall dataset with dimensions {10, 15, 20} f1-Score 0.070 NDCG 0.162 , f1-score 0.071 NDCG 0.168, f1-score 0.073 NDCG 0.173, respectively		
Massaro et al. (2018)	Market basket Analysis with Feed forward Neural network	Data cleaning using the proposed EHC leaner algorithm	Handmade 4 inputs Biscuit, Cold drinks, Tea and Fast food	4 Valid combinations for rainy phase is (1,3,4), (1,3), (1,4) and (3,4)	Source of dataset not mentioned Visualization of data is missing using graph base and scatter plot	Performance plot of FFNN with MBA algorithm Simulation on Transactional dataset
Yu et al. (2016)	Market Basket Analysis using Recurrent Neural Network with Long Short Term Memory	Splitting transactional data into purchase history and shopping cart data	InstaCart Online Grocery Shopping Dataset1 in 2017 206,209 Customer's transaction history including 3,421,083 orders categorizes 49,685 products into 21 departments and 134 aisles	RNN based Personal Purchasing Preference Pattern achieves 18.29% higher Individual Prediction Accuracy than Baseline	Simulation of proposed method using transactional dataset Visualization of data Prediction results of The next item not shown	Performance metrics of proposed method. Real-time marketing strategies using Proposed model
Sreeniasa and Nirmala (2019)	Attention-based neural network	Removed Transactions that contains only one item	Two Real-world transaction dataset IJCAI-15 and Ta-Fang **IJCAI-15:** #Transactions144,936, #Items27,863, Avg. Transaction Length2.91, #Training Transactions 141,840, #Training Instances 412,679, #Testing Transactions 3,096, #Testing Instances 9,030 **Ta-Fang:** #Transactions 19,538, #Items 5,263, Avg. Transaction Length 7.41, #Training Transactions 18,840, #Training Instances 141,768, #Testing Transactions 698, #Testing Instances 3,150	For IJCAI-15Attention Based Transaction Embedding Model performs at REC@10 0.3542, REC@50 0.5134, MRR 0.2041. For Ta-Fang Attention Based Transaction Embedding Model performs at REC@10 0.1089, REC@50 0.2016 , MRR 0.0347.	Proposing Hybrid model using Attention-based mechanism With RNN and CNN	Dataset mentioned with proper dimensions Worked on Recommending novel item other than rigid order assumption using attention mechanism
Lee et al. (2020)	Sequential Hierarchical Attention Network (SHAN)	Items observed by less than 10 users are removed from dataset	T-Mall #user 20,648 #Item 25,129 avg. session length 2.73 #Train session 71,892 #Test session 3,534 Gowalla #user 15,171 #Item 13,193 avg. session length 2.97 #train session 129,225 #Test session 3,635	SHAN performs best on Gowalla dataset with AUC 0.987, Recall 0.439. On the T-Mall dataset SHAN performs best with high AUC 0.801 and SHAN-S	Capturing Feature in long and short term intentions Worked on large datasets	Combining user dynamic long and short term intentions. Hierarchical attention network to capture long and short term intentions.

				performs best with high Recall 0.156 on T-Mall.		Capture high level complex interactions between item-item and user-item factors.
Changchein and Lu (2001)	Multitask Long Short-Term memory-based model	Splitting attributes into four bins morning, afternoon, night, and dawn time splitting data into 90% for training and 10% for testing	InstaCart online grocery shopping cart sales transaction data from 2017 with 3,421,083 millions of orders	LSTM predicted single transaction Embedding of next day purchase accuracy 44%, next hour 56%, and next purchase category 82%. Predicted multiple transactions embedding for the next day 30%, next purchase 57% and purchase category 81% Predicted pre-trained embedding for next day 32%, next hour 62%, and purchase category 82%	An experiment conducted on multi-context embedding using additional dimensions as location, customer age and gender. Use of large dataset to evaluate embedding strategies.	Guide to preprocess customer multi-intention behavior using embedding strategies for customer multi-intent embedding. Multitask LSTM model to learn embedding of multitasking
Changchein and Lu (2001)	Recurrent Neural Network (RNN)	Not mentioned	Real dataset of Fresh Food delivery company with 7716 customers and 10 shopping carts	The LSTM-based recommendation model outperforms the collaborative filtering-based model with an accuracy of 21% high at T and 10% high at T+4.	Use of diverse transactional dataset Proposing hybrid model using CF and RNN based recommendation model	Multi-period product recommender Results mentioned clearly Use of real dataset with proper dimensions
Auon et al. (2015)	Clustering module using neural networks, Self-organization map and rule extraction module using rough set theory	Creating fact table, from database for mining, selecting dimensions and attributes, filtering data with noise and handling missing values Data transformation, normalization	Electronic store dataset for online marketing	using SOM find 9 clusters from O-ID, Buyer, Receiver and product. 99 association rules extracted at minimum confidence 0.25	Applying proposed approach on sales and product dataset considering seasonal effects	Use of the hybrid approach for online recommendation Dimension reduction of dataset

3.2.2. LSTM

Auon et al., (2015) proposed an expectation demonstrate extricating worldly and total highlights utilizing LSTM and QR individually. The novel work is the integration of LSTM and QR models into a Blend of Specialists (ME) to classify rehashed and non-repeated clients.

The tests on the exchange dataset of 9 markets appear that a Blend of Specialists (ME) performs best with less MSE as compared to person Quantile Relapse and LSTM models to classify rehashed and non-repeated clients for 9 markets. For future work, the large dataset can be used to measure the efficiency of the proposed model and use association rules to mine frequently and non-frequently products.

Wang et al., (2016) proposed Multi-Task Representation Learning Demonstrate (MTRLM) to foresee users' statistic properties. The novel work is extricating highlights automatically rather than manually and learning from shared representations. The experiment on a retail dataset of supermarkets shows that MTRL predicts client statistic characteristics from buy history with a tall weighted F1 degree for the medium gather of clients Sex 0.645, Conjugal status 0.802, Instruction Foundation 0.647. For future work Prediction of more demographic attributes to measure the efficiency of the proposed model and use of association rules to find more frequent item sets than the Bag of items method.

Comparatively (Sakar et al, 2019) proposed a cross breed demonstrate utilizing Multilayer Perceptron Organize (MLP) and RNN-LSTM to anticipate the acquiring behavior of clients. The primary module anticipated client deliberates to visit online shops utilizing MLP.

The novel work is utilized filter-based include choice strategies. The MLP beats than base classifiers at a Precision of 87.24, F1-score 0.86, True-positive rate of 0.84 and True-negative rate of 0.92. In the second module, LSTM-RNN estimated visitors' intention to leave the site without a transaction.

Chen & Li, (2019) proposed Consideration Base Repetitive Neural Arrange to suggest a thing for repurchase. The oddity of work is presenting a self-attention component instead of a highlight building base suggestion show. The other recognizing figure is the utilize of LSTM to mine the intermittent buy conduct of clients. The Result appears that AttRNN beats LSTM at a certainty level of 0.2 with an F1 score of 0.4723.

While (Cirqueira et al, 2019) predicted single, multiple, and pre-trained embedding of next day, hour, and purchase category using the LSTM model on InstaCart shopping store. The novel work is a guide to preprocess multi-intent customers using neural network embedding strategies. The result shows that LSTM anticipated single exchange implanting of following day buy exactness at 44%, another hour at 56%, and another buy category at 82%. The LSTM Anticipated numerous exchanges implanting of another day 30%, Following buy 57% and buy category 81%.

The LSTM Anticipated Pre-trained inserting of the following day 32%, following hour 62% and buy category 82%. Long-term work is conducting a Test on Multi setting inserting utilizing extra measurements such as area, client age and sex. The precision of LSTM can be moved forward employing an expansive dataset to assess inserting procedures. The summary table of MBA using LSTM is illustrated in Table 5.

Table 5. Summary Table of MBA using LSTM

Author Year	MBA using AR	Preprocessing	Dataset	Result	Improvement	Good
Wang et al. (2016)	Classification of temporal features using Long Short-Term Memory (LSTM) Classification of aggregate features using Quantile Regression (QR)	Customer-based feature, product-based feature. customer product-based feature extraction	Transaction dataset obtained from Kaggle Acquire Valued Shoppers Challenge with 1-year transaction history of shoppers including 9 markets and 38k customers.	A blend of Specialists (ME) performs best with less MSE as compared to person Quantile Relapse and LSTM strategies to classify rehashed and non-repeated clients for 9 markets.	Use of association rules to mine frequently and non-frequently buying customers Use of a large dataset to measure the efficiency of the proposed model	Integration of deep learning and machine learning methods.
Sakar et al. (2019)	Multi-Task Representation Learning Model (MTRLM) using Feed forward Neural networks	Filtered dataset with items bought by less than 10 times.	BeiRen retail transaction dataset of Chinese supermarkets from 2012 to 2013 with 64097 items, and 80540 users.	MTRL predicts client statistic characteristics from buy history with a tall weighted F1 degree for a medium bunch of clients Sex 0.645, Conjugal status 0.802, Education Background 0.647.	Prediction of more demographic attributes to measure the efficiency of the proposed model. Use of association rules to find frequent item sets than Bag of items representations	Multitask Representation Learning model is based on automatically extracting features than manually defining features

Chen and Li (2019	Multilayer perceptron (MLP), Long Short Term Recurrent Neural Network (LSTM)	Oversampling and feature selection	Online Retail data consisting of 185,000 Web pages visited in 9800 sessions of 3500 visitors.	In the first module, MLP performs best than SVM and Random Forest to predictpurchasing intention of the visitor at an Accuracy of 87.24, F1-score 0.86, positive rate 0.84 and True-negative rate0.92. second module LSTM-RNN estimated visitor intention to leave site without a transaction.	Integrating recommendation system on user or item based.	Real-time customer behavior analysis using a hybrid model.
Cirqueira et al. (2019)	Attention Recurrent Neural Network (AttRNN) Long Short-Term Memory	Not mentioned	InstaCart Dataset with 10,000 shopping records of users, an average of 4 to 100 shopping baskets per user.	attend performs better than LSTM with an F1-score of 0.4723 at a confidence level of 0.2	Hybrid model to mine periodic purchase rules Attention-based mechanism with CNN	Periodic purchase rule Use of self-Attention mechanism
Bai et al. (2019)	Long short-term (LSTM) to predict next recommendation	In Tafeng and BeiRen datasets removed the product bought less than 15 times.	Ta-Feng transaction dataset from December 2000 to 2017 with 7,044 items 1,951 users total 90,986 purchase records. Average purchase record of users 50 average purchase time 14. BeiRen online shopping dataset from April 2013 to July 2013 with 211,519 purchase records 3,264 users and 5,818 items. Purchase record 65. Amazon product from January 1st, 2014 to June 30th, 2014. 6,092 items 1,443 users with 15,811 purchase record average products reviewed by 11.	LSDM performance metrics are On Ta-Feng dataset Hit@5 0.1194, Hit@10 0.1281, NDCG@5 0.0824, NDCG@10 0.0890. On BeiRen dataset Hit@5 0.2187, Hit@10 0.2290, NDCG@5 0.1617, NDCG@10 0.1646. Amazon dataset Hit@5 0.0182, Hit@10 0.0265, NDCG@5 0.0119, NDCG@10 0.0147.	Incorporating attributes of the item as price and category. Detecting best time scale from dataset automatically.	incorporated user's demand towards products over a specific time/ Experiment performed on three real datasets. Considering multiple time scales for long demands using hierarchical neural structure. Use of attention mechanism to capture user's intentions.

5. Conclusions & Future Work

The application of information mining strategies in showcase wicker container investigation is a rising slant in retail. This paper distinguished articles related to advertise wicker container examination in retail distributed between 2000 to 2020. It points to provide an organized survey of showcase wicker container examination in retail utilizing affiliation rules and profound learning strategies.

The restrictions recognized as the require for measurement decrease strategies on the retail dataset utilizing affiliation rules, utilize of consideration, and implanting layers in profound learning strategies on retail datasets to realize more exact comes about. Within the future, more inquire about work is required to create a half breed system due to the developing retail dataset at quick speed and as often as possible changing client buying propensities.

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