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Retail Shop Sales Forecast by Enhanced Feature Extraction with Association Rule Learning

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Abstract— Sales is a basic standpoint for business growth. Demand for consumer products decides the success rate of every business resulting in a profit. Proper analysis of the consumer interest in a particular product decides future sales. The ordinary tactics for sales and promotion objectives no longer help businesses keep up with the speed of a challenging market because it goes out with no knowledge of consumer buying habits. As a consequence of technological developments, significant changes can be seen in the domains of marketing and selling. As a result of such developments, multiple important factors such as consumers' buying habits, target people, and forecasting sales for the coming years can be readily determined, assisting the sales crew in developing strategies to achieve an upsurge in their company. This paper investigates the use of Association Rule Learning with Feature Extraction to forecast sales performance in order to recognise buyers. The consumer's related goods are identified using the association framework. Data on buying activities are derived from purchase invoices provided by the business. The outcome of both is utilized to create a company strategy. Support, Confidence, and Lift are the metrics used for evaluating the quality of association rules produced by the model. Based on the buyers' preferences this paper forecasts retail shop sales and predicts the association relation between the products by feature extraction with Association rule learning to improve future sales. The suggested approach is employed to discover the most common pairings of items found in the business. This will assist with promotion and revenue. This method can help you find intriguing cross-selling and connected goods. The WEKA tool was used to evaluate the correctness of the Association rule that was created.

Keywords- Feature extraction, Association Rule, Support, Confidence, Lift, Sales forecast.

I. INTRODUCTION

In this digital world, every aspect of business needs support from computer-aided techniques to increase their profit and identify their customer needs. The Human brain can't able to store all types of business transactions. To compete in the same field of business and improve customer satisfaction, business society need a strategy. Machine Learning (ML) methods can solve a war between profit and loss. Proper identification of buyer expectations from historical data may increase the sales rate in forthcoming years. Selecting those attributes from a large dataset needs ML techniques. This study utilized feature extraction with Association Rule learning to forecast retail shop sales. The figure below shows the importance of ML algorithms in retail sales forecast prediction.

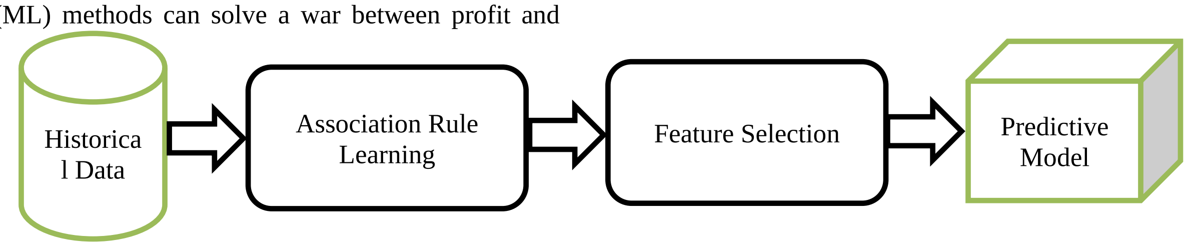

Figure 1. Role of ML in Retail shop Sales Forecast

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This experiment uses a Non-parametric model for prediction, hence it can only be run with strong assumptions. Customer relationship management is utilized here to predict sales at the retail shop. As a result, Apriori for Association rule learning is employed for further analysis in this case. To get the frequent item sets from the transaction dataset, feature extraction and association rules with iterative search are employed in this work. Section 2 provides the literature study, Section 3 displays the approach for predicting retail shop sales, Section 4 summarises the experiment results, and Section 5 concludes with a recommendation for future sales.

II. Literature Review

Nirav et al. proposed a new way to develop frequent items by the Apriori algorithm. This experiment mines and extract feature and form association rule by the Apriori algorithm to predict sales [1]. Pramod et al. used the association rule to extract frequent item patterns from the dataset and used the Apriori algorithm to form an association rule for the retail store sales transaction dataset. This experiment predicts future sales by identifying sales trends and customer behavior [2]. Olagemi et al. experimented with Golden Penny product transaction data and use the Apriori algorithm to mine the strong and valuable rule by association rule and suggest many to improve sales [3].

Grazyna et al. analyzed the behavior of e-customer based on the web server’s log data and identified a high probability of purchasing items by product view and timing slots. Online bookstores were utilized for this analysis. The purchasing probability defines as more than 92% by customer presence in 10 to 25mins and their readability between 30 to 70 pages taken into account [4].

Rathnadiwakara et al. developed a sales prediction model for Alfred ediisingle. The sales prediction used a Decision tree, Association rule, and Naive Bayes algorithms. As a result, Decision tree algorithms performed 98.65%, Association rules performed 100% and Naive Bayes performed 99.5% [5].

Michael et al. proposed a model that took advantage of distinct types of data to improve sales forecasts for a large retailer. The data was taken as daily store-level sales, data broken out by item and retailer-defined customer types. They also utilized retailer-provided store-level demographic data, publicly available regional demographics, and firmographics. The accuracy of this model was less, up to 50% [6].

Patrick et al. researched studying business states using predictive features from (1) publicly available data about the weather and holidays, and (2) data from related products and user data collected for research by food wholesale and retailing firms. The results demonstrates that (1) the ensemble learning approach can perform better than the currently used baseline, (2) it can handle seasonal changes with the ensemble learning better if the feature set for a target product is complemented with features of related product (having similar sales pattern), and (3) an ensemble can become more accurate if information about the weather and holidays is presented explicitly in a feature set [7].

Ritanjali et al. proposed an efficient forecasting model using Differential Evolution (DE) based learning rule. The structure chosen is an adaptive linear combiner whose weights are trained using DE. The prediction performance of the resulting model is evaluated by different months’ retail sales data. These results are compared with the Genetic Algorithm (GA) based approach. The comparison demonstrates improved prediction of sales data by the proposed DE method [8].

Pradip et al. analyzed the changing purchase patterns of shoppers, discovering that the purchasing pattern of shoppers is sometimes influenced by other items purchased. The study offered a method for change mining in which the conditional part may comprise products or items [9].

Ahsan et al. proposed an Artificial Neural Network (ANN) based predictive model to forecast demand in retail shops in Bangladesh. They first analyzed the trend and seasonality patterns of a selected product in a retail trading chain in Bangladesh. Then demand was forecasted using the traditional Holt-Winter model. The same was done again using an ANN with fuzzy uncertainty. Finally, the errors, measured in terms of MAPE, were compared for finding the best-fitting forecasting approach. The research found that the error levels in Holt-Winter’s approach are higher than those obtained through the fuzzy ANN approach and shows the ANN approach provides more accuracy in forecast [10].

Lihong et al. developed a mathematical model based on Markov prediction, it is carried out on empirical research of city car sales in the market and makes a calculation and analysis, it has 99% accuracy [11].

Dilek et al. analyzed to forecast the sales revenue of the grocery retailing industry in Turkey with the help of grocery retailers’ marketing costs, gross profit, and their competitors’ gross profit by using an ANN. This study's predicted results are just 10% larger or smaller than the actual data. Because of this high accuracy, companies in the grocery retailing industry in Turkey can use ANN as a forecasting tool [12].

Anita et al. attempted to understand the retail shop business's driving factors by analyzing sales data from Walmart stores geographically distributed in diverse areas and forecasting sales for 39 weeks. Retail networks are operated efficiently by sales forecasting [13].

Ganhewa et al. researched and studied the relationship between consumer behaviour and product preferences. This study was centred on the fashion retail market, and ML algorithms were applied. The Tree Regression method, Naive

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Bayes algorithm, and K-means algorithm were tested to assess client interest, which aids in retail store sales [17].

Harale et al. utilized ML models K-Neaest Neighbour (KNN), Random Forest (RF), Neural Network (NN), and Naive Bayes (NB) to classify the customer order data. The results were shown that AUC for KNN=0.905, RF=0.933, NN=0.97, and NB=0.97 and identified RF and NN produce a better result than other models. These models help with the creation of automated decision-making systems based on supplier prediction [18].

Sanjay et al. proposed ML algorithms to predict Big Mart sales, including the Generalized Linear Model (GLL), Gradient Boosted Tress (GBT), and Decision Trees. The error rate was evaluated by Root Mean Square Error, Absolute Error, and Mean Square Error. The experiment results show that the accuracy of GBT = 95.84% is higher than, DT = 58.46% and GLL =56.03, and recommend GBT was able to identify the decision which improves the sales [19].

Dogan et al. improved the traditional Association Rule Mining (ARM) by fuzzy set theory. Fuzzy ARM (FARM) considered the sold item and its amount and it collects more information than the traditional method. The results confirmed FARM used fewer rules to produce more information with a confidence threshold value of 0.35 than ARM [20].

Fatoni et al. analyzed purchase data from historical data which is based on online stores. The Apriori identifies the combination of items. It helps in suggesting a product purchase to a consumer, and the association rules yield a 78.92% confidence value when the item combination is taken into account. Finally, this model recommends a suitable product for the customer to purchase [21].

III. Proposed Method

This paper used the dataset from https://archive.ics.uci.edu/ml/datasets/online+retail which contains 541909 instances and 8 attributes. Those Attributes (A) are, A1: Invoice No, A2: Stock Code, A3: Unit Price, Country, and A4: Product Name, A5: Quantity, A6: Invoice Date, A7: Customer ID, A8: Country. Additionally, to evaluate the efficiency of the proposed model, it is tested on one more dataset from https://www.kaggle.com/datasets/sowndarya23/online-retail-dataset and which contains 542014 instances with the same attributes as mentioned above. Feature extraction with Association rule learning was used for the experiment. Following feature extraction, retail shop sales models were forecasted, and the best model for sales prediction was recommended. The following figure 2 shows the overall methodology of the proposed system. Figure 3 shows a few rows of data in the Online Retail dataset.

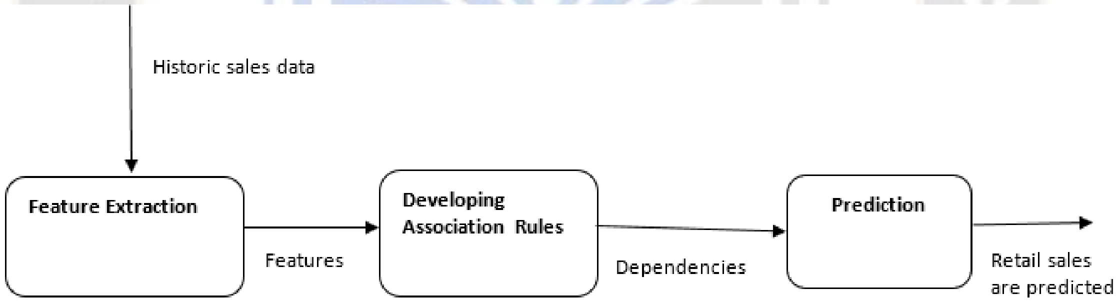

Figure 2. The overall methodology of the proposed system

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	01-12-2010 08:26	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	01-12-2010 08:26	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	01-12-2010 08:26	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	01-12-2010 08:26	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	01-12-2010 08:26	3.39	17850.0	United Kingdom

Figure 3. Dataset head

The frequent pattern mining algorithm was used to discover various item correlations in the dataset.

3.1 Feature Extraction

This approach captures strong and correct features than the previous base model. Proper feature extraction leads to good classification accuracy. Feature extraction removes meaningless and unrelated features from the database or dataset. It finds some low-value features or attributes from the dataset. They are listed as follows:

- Unit price contains a negative value.
- Invoice no has to cancel or return status.
- Quantity shows damaged, lost, and unknown items.
- Some customer ids were containing the null value.

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This study can be utilised for association rule learning to lower the size of the feature subset without affecting accuracy. Create one of the strong attributes of sales.

Sales are simply calculated by sales = quantity * unit price.

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	TotalAmount	Sales
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	01-12-2010 08:26	2.55	17850.0	United Kingdom	15.30	15.30
1	536365	71053	WHITE METAL LANTERN	6	01-12-2010 08:26	3.39	17850.0	United Kingdom	20.34	20.34
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	01-12-2010 08:26	2.75	17850.0	United Kingdom	22.00	22.00
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	01-12-2010 08:26	3.39	17850.0	United Kingdom	20.34	20.34
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	01-12-2010 08:26	3.39	17850.0	United Kingdom	20.34	20.34

Figure 4. Formation of Strong Attribute

3.2 Association Rule Learning

Agrawal et al. developed an Apriori algorithm in 1994 which helps to generate all strong association rules between the items in the database. The association rule is an if-then statement that helps to spot the undiscovered relationship among data. It is a technique for identifying correlations, repeated patterns, and groups of elements that appear together in a table. Association rule can be defined as follows:

Let, Im = {im1,im2,im3,……imn} called set of items, Tr - represents a transaction with a set of items so Tr ⊆ Im, Db – Database. So, the Association rule for items in transaction denotes as A → B, where A ⊂ Im, B ⊂ Im, and A ∩ B = φ.

Two crucial variables that aid in the development of the association rule are confidence and support. It also measures the strength of the association rule. The dataset contains 541909 items and 541909 x 2^{541909} combinations need to create. As a result, the strong association rule only strongly satisfies the minimum support and confidence.

It is one of the famous ML concepts which works under market basket analysis. It is used to discover the relationship between items in a large dataset which helps in identifying the similarity of buyer preferences in large transactions or datasets. Frequent pattern mining algorithms are used to find various item relationships in the dataset and also find irregular data. Apriori is the first algorithm that uses frequent pattern mining. It is a workout by following rules. Let Pb- Probability, Im-Itemset,

- Pb(Im)< minsupport threshold
- Pb(Im+A)< minsupport threshold then Im+A is not frequent
- If Im<minsupport then its superset items are also ignored.

To achieve this apriori uses 2 steps.

- Join step: It creates more items by joining each other.
- Prune step: It counts each item and removes it if it doesn't meet minsupport.

The Association rule works under the concept of Apriori and it needs antecedent and consequent which are termed as items. The IF part of the association rule is called the antecedent and the else part of the association rule is called the consequent. The list of all items is called itemset. Figure 5 depicts an example of an item and an itemset. Itemset = {Bread, Egg, Milk}.

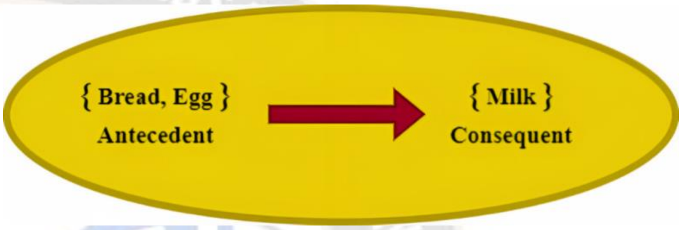

Figure 5. Items and Itemset

A few measures help to build the association rule as follows.

1. Association rule: example $\{A \to B\}$ - finding B on basket A. The following figure 6 shows an example of association rule formation.

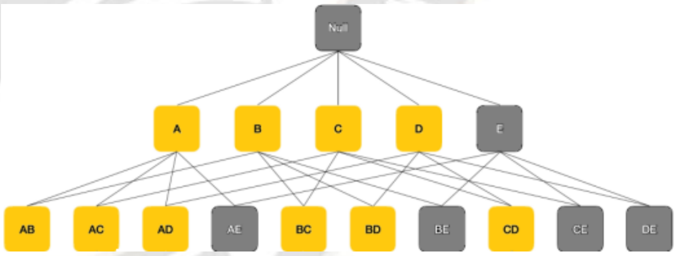

Figure 6. Association rule formation

2. Itemset: example $\{A, B\}$ - list of all items.

3. Support: frequent occurrence of an itemset in all the transactions. It is also used to find the correlations between 2 or more items in the database. Preferred itemsets are easily determined by minimum support threshold.

$$Support(\{A\} \to \{B\}) = \frac{Transactions\ containing\ both\ A\ and\ B}{Total\ number\ of\ transactions}$$

If there are not enough strong support or confidence samples on the dataset then it has been removed by the minimum threshold.

4. Confidence: the probability of $\{B\}$ occurring in given $\{A\}$. It is used to extract high-confidence rules from

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frequent itemsets. So if the consequence is brought because of the Antecedent, then it's a strong rule. If the transaction in A also contains B then confidence,

$$Confidence(\{A\} \rightarrow \{B\}) = \frac{Transactions\ containing\ both\ A\ and\ B}{Transactions\ containing\ A}$$

5. Lift: It is a ratio of confidence to a baseline probability of occurrence of $\{B\}$.

$$Lift(\{A\} \rightarrow \{B\}) = \frac{(Transactions\ containing\ both\ A\ and\ B)/(Tansactions\ containing\ A)}{Fraction\ of\ transactions\ containing\ B}$$

Simply if the sale of B increases the sale of A also increases. It can be defined as follows:

- If Lift(A=>B)=1: No correlation within the itemset.
- If Lift(A=>B)>1: No positive correlation within the itemset.
- If Lift(A=>B)<1: Negative correlation within the itemset.

So, association rule can be formulated by,

1. Frequent itemset generation: All frequent itemsets with support>= pre-determined min support count. So, firstly association of products in the itemset has to find. Example: Itemset = {Bread, Egg, Milk}. Therefore, frequent item sets are found which occurred in the minimum number of times in the transaction and then create rules from the whole list of items to select important ones like an example:{Bread→ Egg, Milk}, {Bread, Egg → Milk}. So frequent itemsets are created by (support>=minsup) with only one item and create itemset length of 2 and then create itemset length of 3 with all possible combinations and find a support value less than min sup and remove it, this process is repeated for all possible items.

From dataset analysis, the following figure 7 shows the number of times the items were bought.

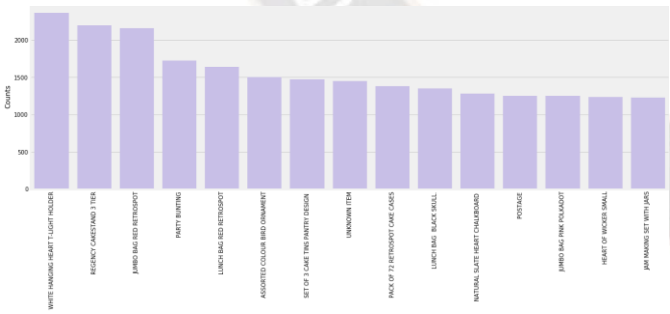

Figure 7. Number of times the items bought

Rule generation: Based on frequent itemset all possible association rules are listed, then support and confidence are calculated for all rules. So, after the itemsets are recognised, rules are generated from all potential item sets, resulting in more rules, not all of which are significant. Identification of rules based on which fall above a minimum confidence level (minconf). In this situation, feature extraction helps to reduce unwanted and meaningless attributes. It develops strong features from the given dataset and helps to get meaningful attributes with higher quality. The candidate rules are formed based on a combination of consequents and repeat this procedure until only one item is left in the antecedent. Association rules are formed as follows:

1. This experiment only evaluates 20 items to determine the association rule, and the quantity of items purchased together must also be determined.
2. The number of invoices from various countries was taken and each country frequently sold items were taken. The sold products from the United Kingdom are depicted in figure 8.

JUMBO BAG RED RETROSPOT	43167
POPCORN HOLDER	34365
ASSORTED COLOUR BIRD ORNAMENT	33679
WHITE HANGING HEART T-LIGHT HOLDER	33193
PACK OF 12 LONDON TISSUES	25307
PACK OF 72 RETROSPOT CAKE CASES	24702
VICTORIAN GLASS HANGING T-LIGHT	23242
BROCADE RING PURSE	22801
ASSORTED COLOURS SILK FAN	20322
PACK OF 60 PINK PAISLEY CAKE CASES	20288
JUMBO BAG PINK POLKADOT	18936
SMALL POPCORN HOLDER	18563
PAPER CHAIN KIT 50'S CHRISTMAS	18197
RED HARMONICA IN BOX	17754
HEART OF WICKER SMALL	17394
PARTY BUNTING	16709
JUMBO BAG STRAWBERRY	16056

Figure 8. Sold items from the United Kingdom

3. The popularity of one product and how to lead sales of another product.
4. TUnpopular items were also identified.
5. Customer interest in purchasing.

The rules which satisfy the minimum support threshold and a minimum confidence threshold are called the strong association rule. Association rule formed by Frequent itemset with min_threshold =1. Lift >=0.6 and confidence >=0.8 then Lift >=0.4 and confidence >=0.8 is used to create rules. These steps are repeated with various values. Following figure 9 shows the correlation between support, confidence, and lift.

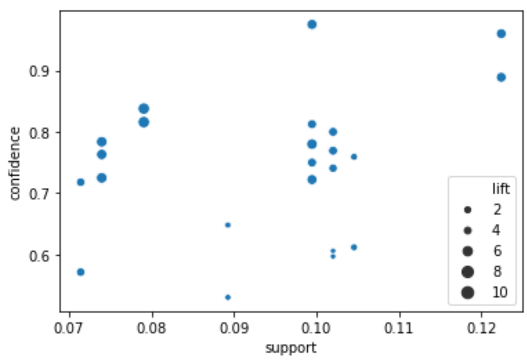

Figure 9. Correlation between Support, Confidence, and Lift

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3.3 *Prediction*

After feature extraction and association rule formulation, prediction has been done. Scheffer defined predictive accuracy as follows:

Let Df be a data file with N number of records. If [A B] is an Association rule then predictive accuracy P of [A B] is defined as C([A B])=P[N] satisfies B/N satisfies A and predictive accuracy is the conditional probability of AN and BN. The association rule prediction was verified by the Weka tool [17].

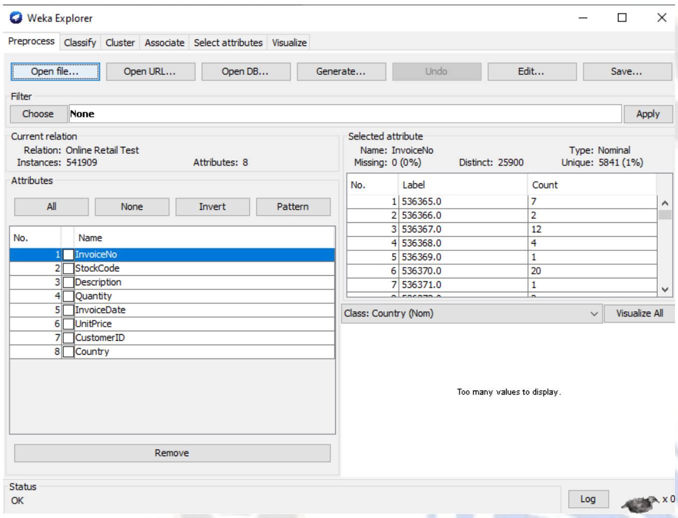

Figure 10. Association rule prediction verified by the weka tool

The following table 1 shows the association rule created for only a few items. P – Product.

Table 1. Association rule for most frequent items

LHS	RHS	Support	Confidence
P1,P2	P1	0.68	0.97
P1, P3	P3	0.69	0.96
P1, P8	P8	0.98	1
P1, P4	P4	0.96	1
P1,P5	P5	0.78	0.99

The following table 2 shows the strongly recommended rules.

Table 2. Strong recommended rule

LHS	RHS	Support	Confidence
P1, P8	P8	0.98	1
P1, P4	P4	0.96	1

This process repeated for every product in the dataset and the final prediction concluded as follows. Highlights of prediction:

The Retail shop sales increased by,

1. Customer preferences
2. Type and nature of the product combination
3. Consider country-wise product preferences

IV. Result And Discussion

Figure 11 shows the sold items from the United Kingdom and Figure 13 shows the unpopular items in the dataset.

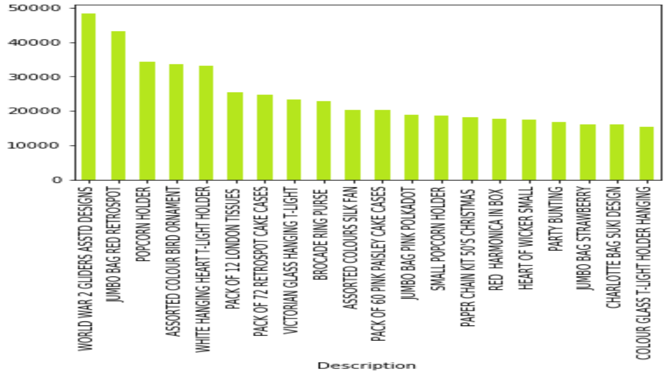

Figure 11. Sold items from the United Kingdom

Following figure 12 shows a correlation between attributes in the dataset.

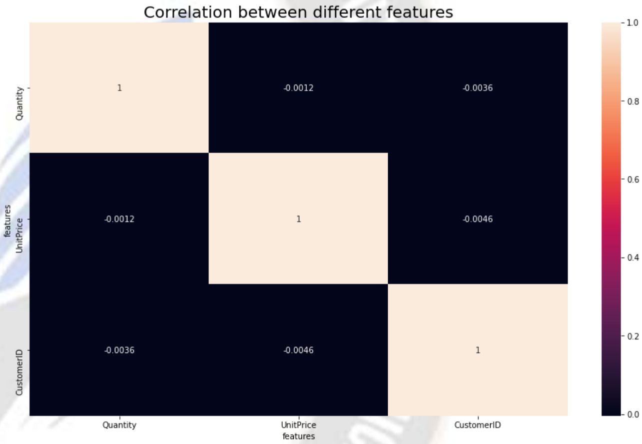

Figure 12. Correlation between attributes in the dataset

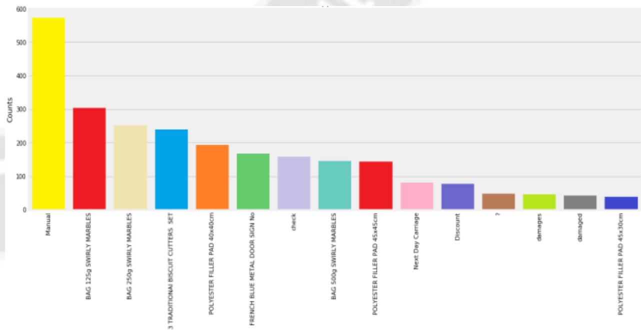

Figure 13. Unpopular items in the dataset

The following figure 14 depicts the various attribute results based on buyer preferences:

WHITE HANGING HEART T-LIGHT HOLDER	2369
REGENCY CAKESTAND 3 TIER	2200
JUMBO BAG RED RETROSPOT	2159
PARTY BUNTING	1727
LUNCH BAG RED RETROSPECT	1638

Figure 14. Most frequently sold items

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V. CONCLUSION

Nowadays retail shops play a dominant role in the business world and it creates an economical war in global marketing. Most stores operate online and should retain enormous volumes of data from day-to-day transactions. It is necessary to understand old and current trends, buyer interest, and demand for the product in digital marketing to find frequent and unique patterns in transactions to hold high profits. Market Basket analysis is one of the ML approaches which helps to create an Association rule for finding the best and worst features in a large collection of the dataset. The work suggests several measures to increase sales. This experiment proposes increasing consumer satisfaction by giving a more comprehensive product catalogue. Customer feedback analysis aids in the improvement of product preferences. Seasonal items should cater to the needs of various countries. As a result, a Retail business may readily adjust this experiment to increase future sales. Various online retail shop datasets will be explored with different ML algorithms in the future to reduce time.

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