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Enhancing Seasonal Sale on Retail Transactions

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Abstract — Retail marketing is the process by which retailers promote awareness and interest of their goods and services in an effort to generate sales from their consumers during a particular season such as Winter, Summer and Monsoon. Retailers capture information on customers purchasing habits which allows them to cater to the needs of the customers. The Weka tool in Data Mining is used for transactional analysis using various classification and association rules. The classification of the dataset is done for each supermarket according to the requirement using the decision tree. The analysis of seasonal sale for retail transactions helps the retailer in mining and obtaining hidden patterns and for increasing sales on less sold items and generating more profits of super store. A comparative study of five supermarkets is then carried out to give knowledge to the retailers on the highest and the least sold items for a particular season.The retailer can then use the knowledge for gaining information about the customer preferences about items during a particular season and can also design promotional offers, discounts etc.

Index Terms— Retail Transactional Data, Data Mining, Classification, J48, Association, FP-Growth, Season, Comparative Study.

1. Introduction

Retail Transactional Data is a very large dataset and consists of many hidden facts and patterns. Data mining is the process of analyzing hidden patterns of data according to different perspectives for categorization into useful information. Data Mining of the retail transactional data set gives the knowledge about the items which are sold more or less, which are sold together, which require advertising or promoting, store layout, stock management of different items during different seasons etc. To acquire this type of knowledge from the large transactional retail dataset, data mining techniques are used. Data mining is used to find out and present useful knowledge from large amounts of data. It is the method in which the data is viewed from different perspectives. As time goes, the volume of data will increase at a fast rate but the useful information will be decreased. So, the primary goal of data mining technique is to find out significant and useful knowledge from the big data set. The purpose of this research paper is to mine the retail transactional data and find out different buying products patterns during a particular season such as winter, summer and monsoon. For this, first classification of the retail transactional data is done into three different classes according to season has been done. After this, association rules for all three classes is performed which gives the frequent item sets in all different

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seasons. This helps in the prediction of the facts about item groups, which one is the most sold and less sold item group in a particular season. It also finds out that which items stocks have to be maintained according to each season. The paper comprises of different sections which eventually fulfills the goal of finding seasonal facts using classification and association techniques. The sections are as follows: Section 2 is about the Literature Survey, Section 3 explains about classification and association techniques, Section 4 gives the dataset used in the research, actual experimentation and analysis is explained in the Section 5, the Comparative Study of five supermarkets is explained in Section 6 and in the last section, I conclude the discussion with the final result.

2. Literature Survey

There are some of researches in the area of data mining of retail industry. Each research gives the facts related with Retail Transactional data that detecting the hidden facts and knowledge.

Pramod Prasad and Dr. Latesh Malik (2011) [1] elaborates upon the use of association rule mining in extracting patterns that occur frequently within a dataset and showcases the implementation of the Apriori algorithm in mining association rules from a dataset containing sales transactions of a retail store.

Alhassan Bala, Mansur Zakariyya Shuaibu,Zaharaddeen Karami Lawal and Rufa'i Yusuf Zakari (2016) [2] discusses about using Weka to compare two algorithms (Apriori and FP-growth) based on execution time and database scan parameters used are; number of instances, confidence and support levels it is categorically clear that FP-Growth algorithm is better than apriori algorithm.

Md. Humayun Kabir (2016) [3] discusses about an approach for generating sales decision making information by analyzing sales data using association rules is more specific decision and application oriented as the business decision makers are not usually interested to all of the items of the sales database for making a specific sales decision.

Ajay Kumar Shrivastava and R. N. Panda (2014) [4] explains the implementation of the Apriori algorithm using WEKA.

Ritu Garg and Preeti Gulia (2015) [5] finds the comparison of Frequent Itemset Mining Algorithms Apriori and FP Growth and which algorithm is better to perform.

3. Classification and Association

Classification is a data mining technique that assigns categories to a collection of data in order to aid in more accurate predictions and analysis. The method divided into two phases: Learning and Classification. In the Learning phase, the training data set has been taken and the analysis has been done on training data set. In the Classification phase, testing has been performed to check the accuracy of the rules. It helps in predicting the future outcomes. From the collected data, the Classification technique helps in classifying the objects according to the class labels. There are classification algorithms like Decision Tree, Neural Network, Rule base Induction etc. Association is a procedure which is meant to find frequent patterns, correlations, associations from data sets found in various kinds of databases such as relational databases, transactional databases, and other forms of data repositories. The rules is like "If the consume bought product x, he/she also bought product y". This means the product y is correlated with the product x. Association rule mining is also known as Market Basket Analysis. There are two major factors in association rule mining, Support and Confidence. The Support of any transaction X is calculated as the proportion of transaction in dataset which contains item set X i.e. SUPP(X) =
X U Y. The confidence is calculated as the proportion of the transactions that contains X which also have Y i.e. CONF(X=>Y) =SUPP (XUY) / SUPP(X). There are many association rule algorithms like Apriori, FP-Growth, Tertius, SETM, etc.

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4. Retail Transactional Dataset of Supermarket

The retail transactional dataset is obtained from the customer's billing information. The dataset consists of attributes such as Bill_No, Bill_Data, Bill_Month, Season, Item_No, Item_Name, Qty, Rate and Amt.In this research, the item groups taken are TEA, SOAP, DETERGENT, SHAMPOO, TOOTHPASTE, AGARBATI etc. The important attribute for the research is the BILL_ DATE. It consists of the date and time, information of the customer purchase of the items. The season for the particular customer transaction is obtained from the bill date information. The bill date consists of the months of the year and has been classified into three quarters. Each quarter represents a different season such as MAR to JUNE is SUMMER season, JULY to OCT is MONSOON season and NOV to FEB is of WINTER season. The data collected is in the form of transactional data set. Each bill_no consists of one or more item groups. So, there is duplication of bill number in the data set. For applying this data set, into Weka tool, the binary format of the data i.e. in form of 1 and 0 is required. For this, each different item group represented as an attribute in the data set. A value of 1 represents presence of item group in the bill and 0 represents absence of item group in the bill. Therefore, as a data preprocessing step, the conversion of transactional data set into binary tabular data set has been done. This tabular data can be easily applied in the Weka tool for association.

5. Result and Discussion

The sample data taken for the research of a supermarket is in Figure 1 shown and the binary transactional dataset in .ARFF file format is given in the Figure 2.

SUPERMARKET_NAME	BILL_NO	BILL_DATE	BILL_MONTH	SEASON	ITEM_NO	ITEM_NAME	QTY	RATE	AMT
SUPERMARKET1	1234	2017-01-01	JAN	WINTER	12011	BISCUIT	8	20	160
SUPERMARKET1	1234	2017-01-01	JAN	WINTER	12012	TEA	3	75	225
SUPERMARKET1	1350	2017-01-05	JAN	WINTER	12013	SOAP	2	20	40
SUPERMARKET1	1350	2017-01-05	JAN	WINTER	12014	DETERGENT	4	15	60
SUPERMARKET1	1456	2017-02-07	FEB	WINTER	12015	SHAMPOO	6	50	300
SUPERMARKET1	1456	2017-02-07	FEB	WINTER	12013	SOAP	5	20	100
SUPERMARKET1	1457	2017-02-07	FEB	WINTER	12017	SUGAR	15	50	750
SUPERMARKET1	1457	2017-02-07	FEB	WINTER	12012	TEA	9	75	675
SUPERMARKET1	1457	2017-02-07	FEB	WINTER	12018	MILK	10	62	620
SUPERMARKET1	1501	2017-03-01	MAR	SUMMER	12015	SHAMPOO	1	50	50
SUPERMARKET1	1501	2017-03-01	MAR	SUMMER	12013	SOAP	2	40	80
SUPERMARKET1	1520	2017-03-15	MAR	SUMMER	12019	BUTTER	1	46	46
SUPERMARKET1	1520	2017-03-15	MAR	SUMMER	12020	BREAD	4	30	120
SUPERMARKET1	1520	2017-03-15	MAR	SUMMER	12021	CHEESE	9	69	621
SUPERMARKET1	1600	2017-04-20	APR	SUMMER	12022	AGARBATI	7	50	350
SUPERMARKET1	1600	2017-04-20	APR	SUMMER	12023	MATCHBOX	4	10	40
SUPERMARKET1	1660	2017-04-25	APR	SUMMER	12026	CHIPS	1	10	10
SUPERMARKET1	1660	2017-04-25	APR	SUMMER	12011	BISCUIT	1	20	20
SUPERMARKET1	3300	2017-08-26	AUG	MONSOON	12022	AGARBATI	12	50	600
SUPERMARKET1	3345	2017-08-30	AUG	MONSOON	12023	MATCHBOX	9	10	90
SUPERMARKET1	3345	2017-08-30	AUG	MONSOON	12022	AGARBATI	3	50	150
SUPERMARKET1	4000	2017-09-28	SEP	MONSOON	12015	SHAMPOO	4	50	200
SUPERMARKET1	4023	2017-09-29	SEP	MONSOON	12024	SOFTDRINK	11	25	275
SUPERMARKET1	4025	2017-09-29	SEP	MONSOON	12015	SHAMPOO	5	50	250
SUPERMARKET1	4025	2017-09-29	SEP	MONSOON	12013	SOAP	6	40	240
SUPERMARKET1	4100	2017-10-15	OCT	MONSOON	12012	TEA	1	75	75
SUPERMARKET1	4100	2017-10-15	OCT	MONSOON	12026	CHIPS	13	10	130
SUPERMARKET1	4040	2017-10-23	OCT	MONSOON	12015	SHAMPOO	5	50	250
SUPERMARKET1	4040	2017-10-23	OCT	MONSOON	12011	BISCUIT	1	20	20
SUPERMARKET1	5000	2017-11-16	NOV	WINTER	12012	TEA	2	75	150
SUPERMARKET1	5000	2017-11-16	NOV	WINTER	12011	BISCUIT	3	10	30
SUPERMARKET1	5030	2017-11-23	NOV	WINTER	12012	TEA	3	75	225
SUPERMARKET1	5030	2017-11-23	NOV	WINTER	12011	BISCUIT	1	20	20
SUPERMARKET1	6000	2017-12-12	DEC	WINTER	12014	DETERGENT	1	15	15
SUPERMARKET1	6001	2017-12-12	DEC	WINTER	12014	DETERGENT	2	15	30
SUPERMARKET2	1200	2017-01-04	JAN	WINTER	13001	COFFEE	1	125	125
SUPERMARKET2	1200	2017-01-04	JAN	WINTER	13002	BISCUIT	2	30	60
SUPERMARKET2	1250	2017-01-10	JAN	WINTER	13003	TEA	6	150	900

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SUPERMARKET2	1340	2017-02-24	FEB	WINTER	13003	TEA	3	150	450
SUPERMARKET2	1340	2017-02-24	FEB	WINTER	13001	COFFEE	1	125	125
SUPERMARKET2	1345	2017-02-24	FEB	WINTER	13005	KETCHUP	4	75	300
SUPERMARKET2	1345	2017-02-24	FEB	WINTER	13001	COFFEE	1	125	125
SUPERMARKET2	1450	2017-03-13	MAR	SUMMER	13010	JUICE	4	20	80
SUPERMARKET2	1450	2017-03-13	MAR	SUMMER	13007	SOFTDRINK	6	25	150
SUPERMARKET2	1451	2017-03-13	MAR	SUMMER	13004	SHAMPOO	3	50	150
SUPERMARKET2	1480	2017-03-25	MAR	SUMMER	13008	BREAD	2	25	50
SUPERMARKET2	1480	2017-03-25	MAR	SUMMER	13009	BUTTER	1	46	46
SUPERMARKET2	1582	2017-04-25	APR	SUMMER	13010	JUICE	5	20	100
SUPERMARKET2	1582	2017-04-25	APR	SUMMER	13007	SOFTDRINK	3	25	75
SUPERMARKET2	1600	2017-04-31	APR	SUMMER	13011	SOAP	1	40	40
SUPERMARKET2	1600	2017-04-31	APR	SUMMER	13003	TEA	3	150	450
SUPERMARKET2	1651	2017-05-04	MAY	SUMMER	13007	SOFTDRINK	5	25	125
SUPERMARKET2	1651	2017-05-04	MAY	SUMMER	13010	JUICE	2	20	40
SUPERMARKET2	1670	2017-05-10	MAY	SUMMER	13012	AGARBATI	3	70	210
SUPERMARKET2	1720	2017-06-15	JUNE	SUMMER	13006	BREAD	2	30	60
SUPERMARKET2	1720	2017-06-15	JUNE	SUMMER	13013	SUGAR	4	50	200
SUPERMARKET2	1720	2017-06-25	JUNE	SUMMER	13014	MILKSHAKE	4	20	80
SUPERMARKET2	1770	2017-06-25	JUNE	SUMMER	13011	SOAP	4	40	160
SUPERMARKET2	1856	2017-07-18	JULY	MONSOON	13015	DETERGENT	1	15	15
SUPERMARKET2	1856	2017-07-18	JULY	MONSOON	13016	TOOTHPASTE	10	48	480
SUPERMARKET2	1857	2017-07-18	JULY	MONSOON	13004	SHAMPOO	6	50	300
SUPERMARKET2	1857	2017-07-18	JULY	MONSOON	13015	DETERGENT	1	15	15
SUPERMARKET2	1920	2017-08-22	AUG	MONSOON	13016	TOOTHPASTE	12	48	576
SUPERMARKET2	1920	2017-08-22	AUG	MONSOON	13011	SOAP	3	40	120
SUPERMARKET3	1220	2017-02-12	FEB	WINTER	10005	SHAMPOO	5	50	250
SUPERMARKET3	1278	2017-02-12	FEB	WINTER	10019	BISCUIT	10	20	200
SUPERMARKET3	1278	2017-02-21	FEB	WINTER	10006	COFFEE	7	125	875
SUPERMARKET3	1330	2017-03-15	MAR	SUMMER	10007	JUICE	11	50	550
SUPERMARKET3	1330	2017-03-15	MAR	SUMMER	10008	CHIPS	8	10	80
SUPERMARKET3	1400	2017-03-25	MAR	SUMMER	10009	TEA	9	150	1350
SUPERMARKET3	1400	2017-03-25	MAR	SUMMER	10010	MILK	8	62	496
SUPERMARKET3	1489	2017-03-30	MAR	SUMMER	10019	BISCUIT	9	20	180
SUPERMARKET3	1489	2017-03-30	MAR	SUMMER	10011	MILKSHAKE	5	20	100
SUPERMARKET3	1590	2017-04-21	APR	SUMMER	10013	JAM	6	130	780
SUPERMARKET3	1590	2017-04-21	APR	SUMMER	10002	BREAD	8	30	240
SUPERMARKET3	1680	2017-04-28	APR	SUMMER	10012	AGARBATI	8	70	560
SUPERMARKET3	1680	2017-04-28	APR	SUMMER	10013	MATCHBOX	10	10	100
SUPERMARKET3	1730	2017-05-12	MAY	SUMMER	10019	BISCUIT	1	20	20
SUPERMARKET3	1730	2017-05-12	MAY	SUMMER	10011	MILKSHAKE	5	20	100
SUPERMARKET3	1731	2017-05-12	MAY	SUMMER	10004	SOAP	8	40	320
SUPERMARKET3	1731	2017-05-12	MAY	SUMMER	10005	SHAMPOO	10	50	500
SUPERMARKET3	1900	2017-05-25	MAY	SUMMER	10014	SUGAR	10	50	500
SUPERMARKET3	2300	2017-06-10	JUNE	SUMMER	10015	DETERGENT	7	15	105
SUPERMARKET3	2300	2017-06-10	JUNE	SUMMER	10004	SOAP	1	40	40
SUPERMARKET3	2360	2017-06-15	JUNE	SUMMER	10019	BISCUIT	1	20	20
SUPERMARKET3	2360	2017-06-15	JUNE	SUMMER	10011	MILKSHAKE	6	20	120
SUPERMARKET3	2361	2017-06-15	JUNE	SUMMER	10008	CHIPS	2	10	20
SUPERMARKET3	2361	2017-06-15	JUNE	SUMMER	10006	COFFEE	5	125	625
SUPERMARKET3	2500	2017-07-21	JULY	MONSOON	10018	CHEESE	12	69	828
SUPERMARKET3	3005	2017-09-16	SEP	MONSOON	10004	SOAP	3	40	120
SUPERMARKET3	3005	2017-09-16	SEP	MONSOON	10005	SHAMPOO	17	50	850
SUPERMARKET3	3121	2017-09-16	SEP	MONSOON	10013	MATCHBOX	1	10	10
SUPERMARKET3	3121	2017-09-16	SEP	MONSOON	10012	AGARBATI	4	70	280
SUPERMARKET3	3200	2017-09-05	SEP	MONSOON	10013	MATCHBOX	2	10	20
SUPERMARKET3	3200	2017-10-05	OCT	MONSOON	10016	CANDLE	2	10	20
SUPERMARKET3	3272	2017-10-11	OCT	MONSOON	10001	SOUP	4	60	240
SUPERMARKET3	3300	2017-11-11	NOV	WINTER	10006	COFFEE	4	125	500
SUPERMARKET3	3300	2017-11-11	NOV	WINTER	10019	BISCUIT	1	20	20
SUPERMARKET3	3380	2017-11-15	NOV	WINTER	10006	COFFEE	2	125	250
SUPERMARKET3	3380	2017-11-15	NOV	WINTER	10019	BISCUIT	5	20	100
SUPERMARKET3	3380	2017-12-17	DEC	WINTER	10007	JUICE	16	50	800
SUPERMARKET3	3420	2017-12-17	DEC	WINTER	10019	BISCUIT	3	20	60
SUPERMARKET3	3420	2017-12-17	DEC	WINTER	10006	COFFEE	2	125	250
SUPERMARKET3	3510	2017-12-21	DEC	WINTER	10015	DETERGENT	8	15	120
SUPERMARKET4	1200	2017-01-05	JAN	WINTER	1009	TEA	10	150	1500
SUPERMARKET4	1200	2017-01-05	JAN	WINTER	1001	BISCUIT	2	70	140
SUPERMARKET4	1250	2017-01-21	JAN	WINTER	1002	SOUP	1	60	60
SUPERMARKET4	1250	2017-01-21	JAN	WINTER	1003	BREAD	2	30	60
SUPERMARKET4	1310	2017-02-17	FEB	WINTER	1004	SOAP	2	40	80
SUPERMARKET4	1310	2017-02-15	FEB	WINTER	1005	SHAMPOO	1	50	50
SUPERMARKET4	1350	2017-02-20	FEB	WINTER	1006	KETCHUP	6	75	450
SUPERMARKET4	1351	2017-02-20	FEB	WINTER	1009	TEA	2	150	300
SUPERMARKET4	1410	2017-03-01	MAR	SUMMER	1007	ICECREAM	4	30	120
SUPERMARKET4	1410	2017-03-01	MAR	SUMMER	1008	SOFTDRINK	2	25	50
SUPERMARKET4	1480	2017-03-21	MAR	SUMMER	1006	KETCHUP	3	75	225
SUPERMARKET4	1480	2017-03-21	MAR	SUMMER	1008	CHIPS	1	10	10

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SUPERMARKET4	2121	2017-06-29	JUNE	SUMMER	1007	ICECREAM	3	30	90
SUPERMARKET4	2121	2017-06-29	JUNE	SUMMER	1100	SOFTDRINK	2	25	50
SUPERMARKET4	2180	2017-07-15	JULY	MONSOON	1007	SOAP	9	40	360
SUPERMARKET4	2180	2017-07-15	JULY	MONSOON	1005	SHAMPOO	9	50	450
SUPERMARKET4	2200	2017-07-22	JULY	MONSOON	1011	AGARBATI	1	70	70
SUPERMARKET4	2200	2017-07-22	JULY	MONSOON	1015	CANDLE	6	10	60
SUPERMARKET4	2270	2017-07-26	JULY	MONSOON	1003	BREAD	9	30	270
SUPERMARKET4	2430	2017-08-23	AUG	MONSOON	1000	HOT_CHOCOLATE	2	150	300
SUPERMARKET4	2430	2017-08-23	AUG	MONSOON	1001	BISCUIT	11	70	770
SUPERMARKET4	2431	2017-08-23	AUG	MONSOON	1003	BREAD	5	30	150
SUPERMARKET4	2800	2017-09-29	SEP	MONSOON	1007	SOAP	8	40	320
SUPERMARKET4	2800	2017-09-29	SEP	MONSOON	1005	SHAMPOO	10	50	500
SUPERMARKET4	2801	2017-09-29	SEP	MONSOON	1011	AGARBATI	13	70	910
SUPERMARKET4	2801	2017-09-29	SEP	MONSOON	1015	CANDLE	8	10	80
SUPERMARKET4	3000	2017-10-10	OCT	MONSOON	1015	CANDLE	3	10	30
SUPERMARKET4	3000	2017-10-10	OCT	MONSOON	1012	MATCHBOX	15	10	150
SUPERMARKET4	3150	2017-10-21	OCT	MONSOON	1000	HOT_CHOCOLATE	11	150	1650
SUPERMARKET4	3150	2017-10-21	OCT	MONSOON	1001	BISCUIT	3	70	210
SUPERMARKET4	3300	2017-11-15	NOV	WINTER	1009	TEA	3	150	450
SUPERMARKET4	3310	2017-11-15	NOV	WINTER	1011	AGARBATI	6	70	420
SUPERMARKET4	3380	2017-11-15	NOV	WINTER	1009	TEA	3	150	450
SUPERMARKET4	3380	2017-11-15	NOV	WINTER	1001	BISCUIT	1	70	70
SUPERMARKET5	1381	2017-02-04	FEB	WINTER	1115	BREAD	5	30	150
SUPERMARKET5	1381	2017-02-04	FEB	WINTER	1116	MILK	8	62	496
SUPERMARKET5	1410	2017-02-15	FEB	WINTER	1117	AGARBATI	8	70	560
SUPERMARKET5	1500	2017-03-25	MAR	SUMMER	1121	ICECREAM	3	30	90
SUPERMARKET5	1500	2017-03-25	MAR	SUMMER	1112	CHIPS	1	10	10
SUPERMARKET5	1550	2017-03-28	MAR	SUMMER	1119	SHAMPOO	4	50	200
SUPERMARKET5	1550	2017-03-28	MAR	SUMMER	1120	DETERGENT	4	15	60
SUPERMARKET5	1630	2017-04-15	APR	SUMMER	1121	ICECREAM	5	30	150
SUPERMARKET5	1630	2017-04-15	APR	SUMMER	1112	CHIPS	1	10	10
SUPERMARKET5	1680	2017-04-25	APR	SUMMER	1123	JAM	5	130	650
SUPERMARKET5	1680	2017-04-25	APR	SUMMER	1124	BUTTER	1	46	46
SUPERMARKET5	1730	2017-05-30	MAY	SUMMER	1125	MILKSHAKE	5	20	100
SUPERMARKET5	1800	2017-05-14	MAY	SUMMER	1121	ICECREAM	3	10	30
SUPERMARKET5	1801	2017-05-14	MAY	SUMMER	1120	DETERGENT	5	15	75
SUPERMARKET5	1860	2017-05-18	MAY	SUMMER	1126	TEA	4	75	300
SUPERMARKET5	1940	2017-06-12	JUNE	SUMMER	1121	ICECREAM	6	30	180
SUPERMARKET5	1940	2017-06-12	JUNE	SUMMER	1112	CHIPS	5	10	50
SUPERMARKET5	1941	2017-06-12	JUNE	SUMMER	1127	FROZEN_SNACKS	6	150	900
SUPERMARKET5	1941	2017-06-12	JUNE	SUMMER	1128	KETCHUP	4	75	300
SUPERMARKET5	2000	2017-07-21	JULY	MONSOON	1111	INSTANT_NOODLES	8	30	240
SUPERMARKET5	2000	2017-07-21	JULY	MONSOON	1112	CHIPS	3	10	30
SUPERMARKET5	2001	2017-07-21	JULY	MONSOON	1114	DETERGENT	2	15	30
SUPERMARKET5	2100	2017-08-21	AUG	MONSOON	1111	INSTANT_NOODLES	9	30	270
SUPERMARKET5	2100	2017-08-21	AUG	MONSOON	1128	KETCHUP	12	75	900
SUPERMARKET5	2100	2017-08-21	AUG	MONSOON	1112	CHIPS	9	10	90
SUPERMARKET5	2110	2017-08-21	AUG	MONSOON	1129	CANDLE	3	10	30
SUPERMARKET5	2180	2017-09-03	SEP	MONSOON	1130	SOUP	12	60	720

Figure 1: Retail Transactional Dataset

Supermarketv1_winter_1.arff

Relation: Supermarketv1_winter_1

No.	1: TEA Nominal	2: BISCUIT Nominal	3: SOAP Nominal	4: DETERGENT Nominal	5: SHAMPOO Nominal	6: SUGAR Nominal	7: MILK Nominal
1	1	1	0	0	0	0	0
2	0	0	1	1	0	0	0
3	0	0	1	0	1	0	0
4	1	0	0	0	0	1	1
5	1	1	0	0	0	0	0
6	1	1	0	0	0	0	0
7	0	0	0	1	0	0	0
8	0	0	0	1	0	0	0

Supermarketv2_summer_2.arff

Relation: Supermarketv2_summer_2

No.	1: SOFTDRINK Nominal	2: MILKSHAKE Nominal	3: SHAMPOO Nominal	4: BREAD Nominal	5: BUTTER Nominal	6: JUICE Nominal	7: SOAP Nominal	8: TEA Nominal	9: AGARBATI Nominal	10: SUGAR Nominal
1	1	0	0	0	0	1	0	0	0	0
2	0	0	1	0	0	0	0	0	0	0
3	0	0	0	1	1	0	0	0	0	0
4	1	0	0	0	0	1	0	0	0	0
5	0	0	0	0	0	0	1	1	0	0
6	1	0	0	0	0	1	0	0	0	0
7	0	0	0	0	0	0	0	0	1	0
8	0	1	0	1	0	0	0	0	0	1

Supermarketv2_monsoon_2.arff

Relation: Supermarketv2_monsoon_2

No.	1: SHAMPOO Nominal	2: DETERGENT Nominal	3: TOOTHPASTE Nominal	4: SOAP Nominal	5: COFFEE Nominal	6: BUTTER Nominal	7: JAM Nominal	8: BISCUIT Nominal
1	0	1	1	0	0	0	0	0
2	1	1	0	0	0	0	0	0
3	0	1	1	1	0	0	0	0
4	0	0	0	0	1	0	0	1
5	1	1	0	0	0	0	0	0
6	0	0	0	0	0	1	1	0
7	1	1	0	0	0	0	0	0
8	0	0	0	0	1	0	0	1
9	0	1	0	0	0	0	0	0

Supermarketv1_summer_1.arff

Relation: Supermarketv1_summer_1

No.	1: SHAMPOO Nominal	2: SOAP Nominal	3: BUTTER Nominal	4: BREAD Nominal	5: CHEESE Nominal	6: AGARBATI Nominal	7: MATCHBOX Nominal	8: SOFTDRINK Nominal	9: CHIPS Nominal	10: BISCUIT Nominal
1	1	1	0	0	0	0	0	0	0	0
2	0	0	1	1	1	0	0	0	0	0
3	0	0	0	0	0	1	1	0	0	0
4	0	0	0	0	0	0	0	1	1	1
5	0	0	0	0	0	0	0	1	1	1
6	1	1	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	1	1	1

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Supermarketv3_winter_3.arff

Relation: Supermarketv3_winter_3

No.	1: SOUP	2: BREAD	3: KETCHUP	4: SOAP	5: DETERGENT	6: SHAMPOO	7: BISCUIT	8: COFFEE	9: JUICE
	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
1	1	1	0	0	0	0	0	0	0
2	0	1	1	0	0	0	0	0	0
3	1	1	0	0	0	0	0	0	0
4	0	0	0	1	1	1	0	0	0
5	0	0	0	0	0	0	1	1	0
6	0	0	0	0	0	0	1	1	0
7	0	0	0	0	0	0	1	1	1
8	0	0	0	0	0	0	1	1	0
9	0	0	0	0	1	0	0	0	0

Supermarketv2_winter_2.arff

Relation: Supermarketv2_winter_2

No.	1: COFFEE	2: BISCUIT	3: TEA	4: SHAMPOO	5: KETCHUP	6: BREAD	7: JAM	8: MILK
	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
1	1	1	0	0	0	0	0	0
2	0	1	1	0	0	0	0	0
3	1	0	1	0	0	0	0	0
4	1	0	0	0	1	0	0	0
5	1	0	0	0	1	0	0	0
6	1	0	0	0	1	0	0	0
7	0	0	0	0	0	0	0	1
8	1	0	1	1	0	0	0	0

Supermarketv3_summer_3.arff

Relation: Supermarketv3_summer_3

No.	1: JUICE	2: CHIPS	3: TEA	4: MILK	5: MILKSHAKE	6: JAM	7: BREAD	8: AGARBATI	9: MATCHBOX	10: SOAP	11: SHAMPOO	12: SUGAR
	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
1	1	1	0	0	0	0	0	0	0	0	0	0
2	0	0	1	1	0	0	0	0	0	0	0	0
3	0	0	0	0	1	1	0	0	0	0	0	0
4	0	0	0	0	0	0	1	1	0	0	0	0
5	0	0	0	0	0	0	0	0	1	1	0	0
6	0	0	0	0	1	1	0	0	0	0	0	0
7	0	0	0	0	0	0	0	0	0	0	1	1
8	0	0	0	0	0	0	0	0	0	0	1	0
9	0	0	0	0	1	1	0	0	0	0	0	0
10	0	1	0	0	0	0	0	0	0	0	0	0

Supermarketv3_monsoon_3.arff

Relation: Supermarketv3_monsoon_3

No.	1: COFFEE	2: CANDLE	3: MATCHBOX	4: DETERGENT	5: TOOTHPASTE	6: SOAP	7: SHAMPOO	8: AGARBATI	9: SOUP	10: CHEESE
	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
1	1	0	0	0	0	0	0	0	0	1
2	1	0	0	0	0	0	0	0	0	0
3	0	0	0	1	1	0	0	0	0	0
4	0	0	0	1	1	0	0	0	0	0
5	0	0	0	0	1	0	0	0	0	0
6	0	1	1	0	0	0	0	0	0	0
7	0	0	0	0	0	1	1	0	0	0
8	0	0	1	0	0	0	0	1	0	0
9	0	1	1	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	1	0

Supermarketv4_winter_4.arff

Relation: Supermarketv4_winter4

No.	1: TEA	2: BISCUIT	3: SOUP	4: BREAD	5: SOAP	6: SHAMPOO	7: KETCHUP	8: AGARBATI	9: DETERGENT
	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
1	1	1	0	0	0	0	0	0	0
2	0	0	1	1	0	0	0	0	0
3	0	0	0	0	1	1	0	0	0
4	0	0	0	0	0	0	1	0	0
5	1	0	0	0	0	0	0	0	0
6	1	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	0	1	0
8	1	1	0	0	0	0	0	0	0
9	0	0	1	1	0	0	0	0	0
10	0	0	0	0	1	0	0	0	1

Supermarketv4_summer_4.arff

Relation: Supermarketv4_summer4

No.	1: ICECREAM	2: SOFTDRINK	3: KETCHUP	4: CHIPS	5: TEA	6: AGARBATI	7: MATCHBOX	8: MILKSHAKE	9: SOAP	10: DETERGENT
	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
1	1	1	0	0	0	0	0	0	0	0
2	0	0	1	1	0	0	0	0	0	0
3	0	0	0	0	1	0	0	0	0	0
4	1	1	0	0	0	0	0	0	0	0
5	0	0	0	0	0	1	1	0	0	0
6	0	0	0	0	0	0	0	1	0	0
7	0	0	0	0	0	0	0	0	1	1
8	0	0	0	0	0	1	1	0	0	0
9	1	0	0	0	0	0	0	1	0	0

Supermarketv4_monsoon_4.arff

Relation: Supermarketv4_monsoon_4

No.	1: SOAP	2: SHAMPOO	3: AGARBATI	4: CANDLE	5: HOT_CHOCOLATE	6: BISCUIT	7: BREAD	8: MATCHBOX
	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
1	1	1	0	0	0	0	0	0
2	0	0	1	1	0	0	0	0
3	0	0	0	0	0	0	1	0
4	0	0	0	0	1	1	0	0
5	0	0	0	0	0	0	1	0
6	1	1	0	0	0	0	0	0
7	0	0	1	1	0	0	0	0
8	0	0	0	1	0	0	0	1
9	0	0	0	0	1	1	0	0

Supermarketv5_winter_5.arff

Relation: Supermarketv5_winter5

No.	1: INSTANT_NOODLES	2: CHIPS	3: COFFEE	4: BREAD	5: MILK	6: AGARBATI	7: MIXED_SPICES	8: TEA	9: BISCUIT	10: SHAMPOO
	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal	Nominal
1	1	1	0	0	0	0	0	0	0	0
2	0	0	1	1	0	0	0	0	0	0
3	1	0	0	0	0	0	0	0	0	0
4	0	0	0	1	1	0	0	0	0	0
5	0	0	0	0	0	1	0	0	0	0
6	0	0	0	0	0	0	1	1	0	0
7	0	0	1	0	0	0	0	0	1	0
8	0	0	0	0	0	0	1	1	0	0
9	0	0	0	0	0	1	0	0	0	1

Figure 2: Binary Transactional Dataset

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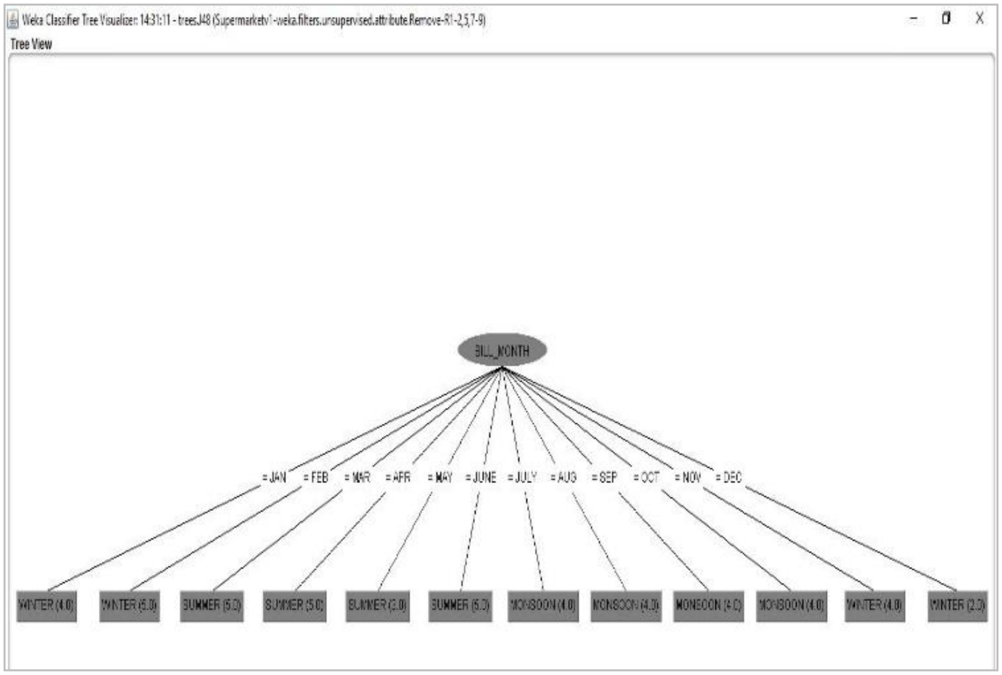

Figure 3: Bill Month Season Wise Classification for Supermarket1

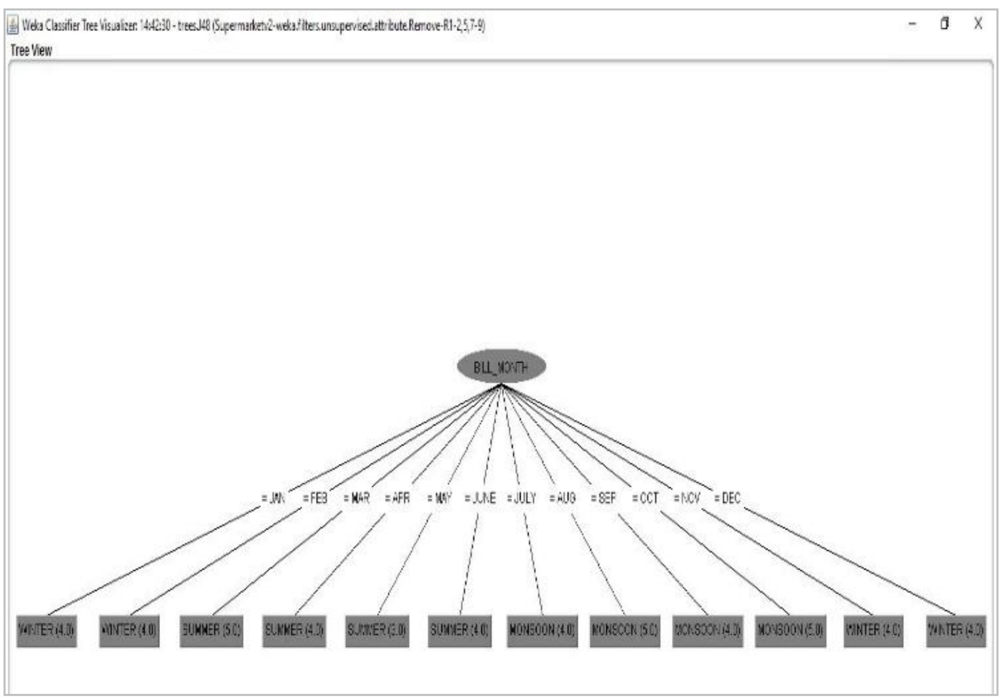

Figure 4: Bill Month Season Wise Classification For Supermarket2

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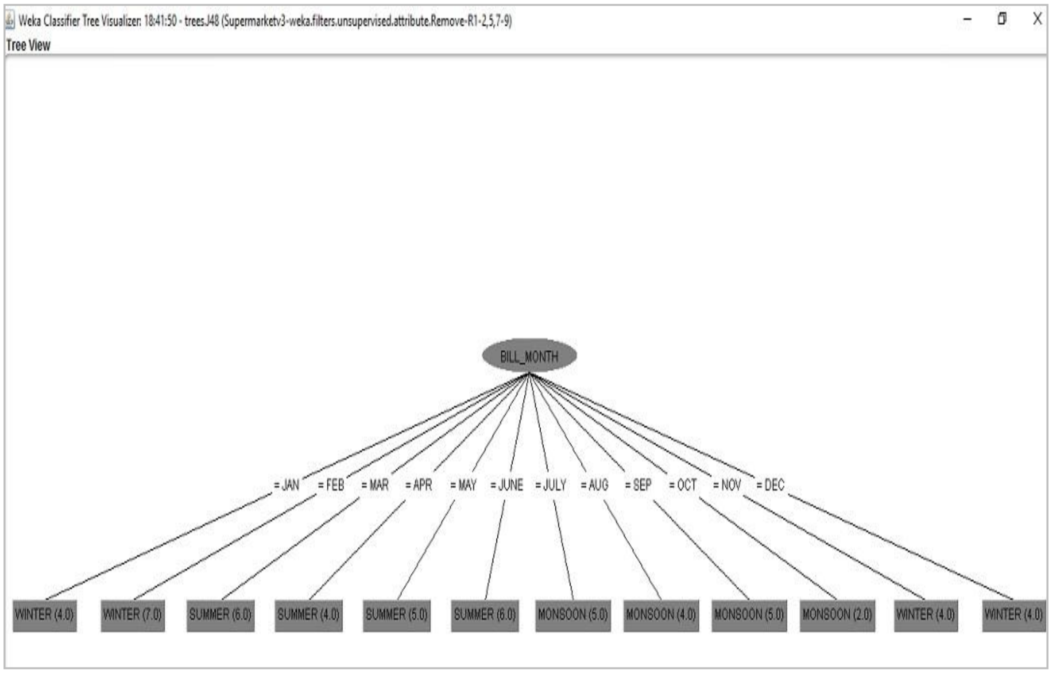

Figure 5: Bill Month Season Wise Classification for Supermarket 3

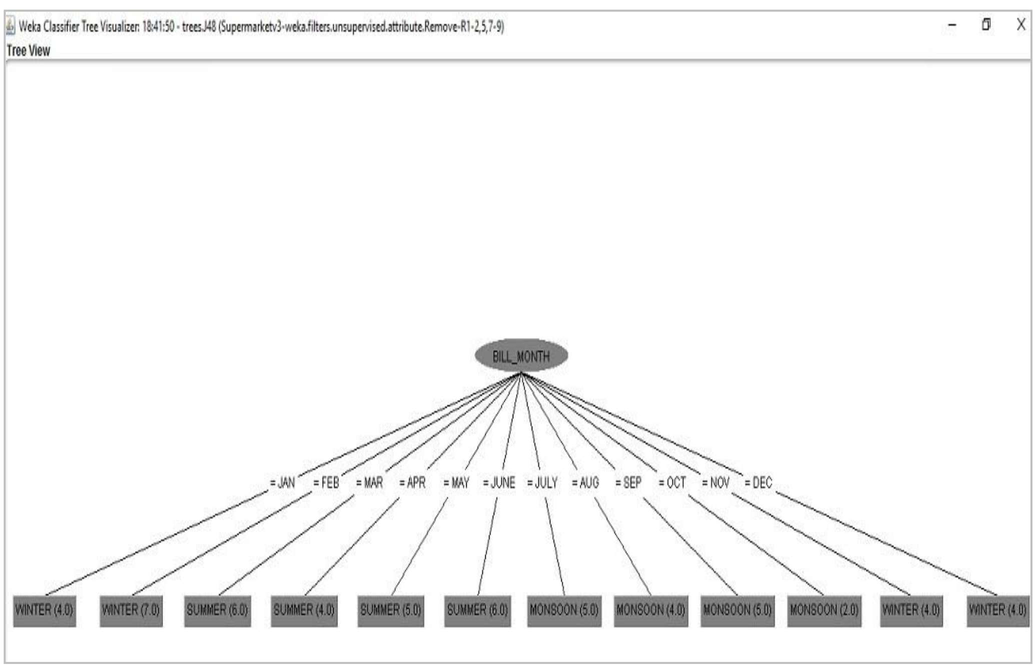

Figure 6: Bill Month Season Wise Classification for Supermarket4

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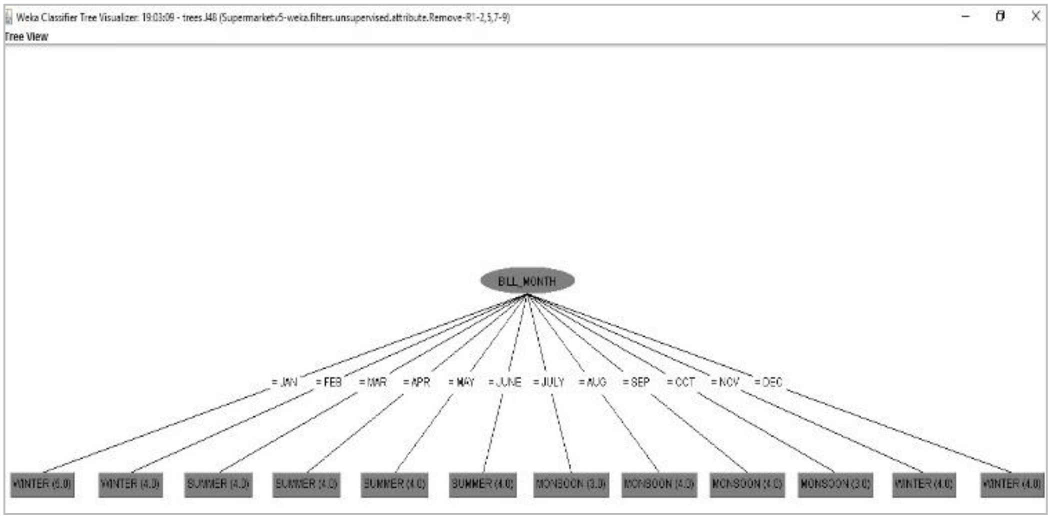

Figure 7: Bill Month Season Wise Classification for Supermarket 5

The seasonal analysis of the retail transactional dataset has been done by the classification of data into three different classes SUMMER, MONSOON and WINTER for every supermarket. The classification analysis is useful for retailer to maintain stock of particular item group in particular season, to plan sale according to season, design promotional offers, discounts on least sold items etc. The classification of the whole data set is done according to bill month, using J48 decision tree algorithm. J48 is the cost effective option than the other classification algorithms. The decision tree made by the J48 decision tree algorithm is displayed in the Figure 3 for supermarket 1, Figure 4 for supermarket 2, Figure 5 for supermarket 4 and Figure 6 for supermarket 4 and Figure 7 for supermarket 5. After classification of the data, the highest and least sold item for every season in each of the five supermarkets is found out. The bar charts in Figure 8, Figure 9, Figure 10, Figure 11 and Figure 12 represents the highest and least sold items in supermarket 1, supermarket 2, supermarket 3, supermarket 4 and supermarket 5 respectively. The bar chart clearly displays the effect of season on item group.

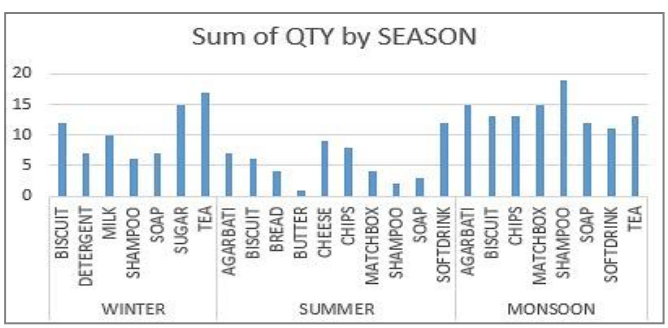

Figure 8: Highest And Least Sold Items in Supermarket 1

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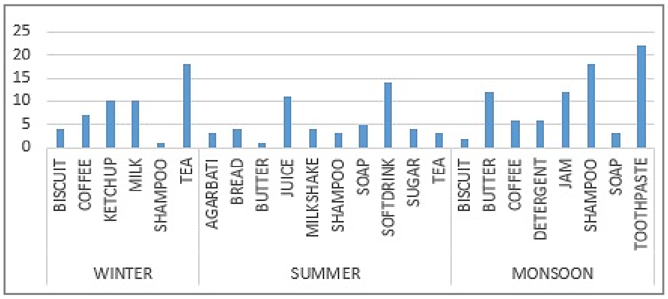

Figure 9: Highest and Least Sold Items in Supermarket 2

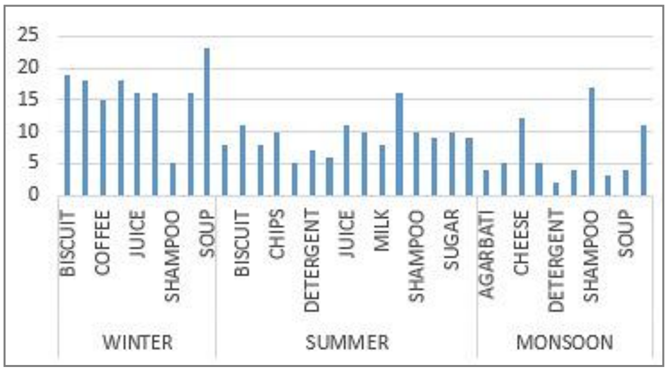

Figure 10: Highest and Least Sold Items in Supermarket 3

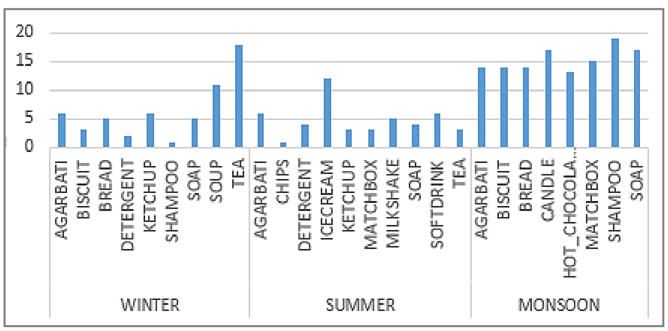

Figure 11: Highest And Least Sold Items in Supermarket 4

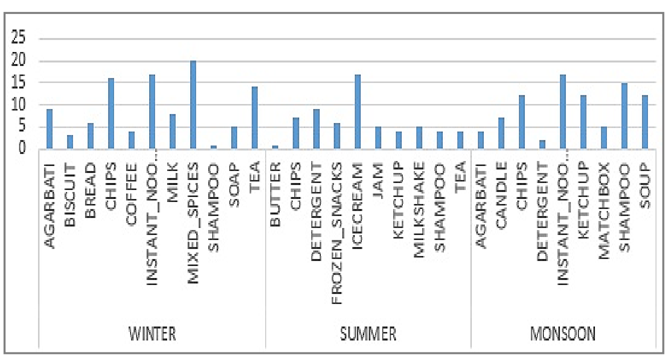

Figure 12: Highest And Least Sold Items in Supermarket 5

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The bar charts clearly represents that MONSOON season has highest selling season for maximum item groups. Those groups are highest selling season for maximum item groups. Those groups are SHAMPOO, SOAP, TOOTHPASTE etc. DETERGENT is more used in WINTER, than in SUMMER and last in MONSOON. After finding the highest and least sold from the retail transactional dataset the pair or triplets of item groups, which were sold together have to be found.

The correlation between item groups, is performed using association rule mining. The association of different item groups has been achieved using FP Growth algorithm. The FP-Growth algorithm is chosen due to its fast execution and no candidate generation. This algorithm has been applied on different season data set by calculating the minimum confidence and minimum support of each transaction.

The association rules for each season in each of the five supermarkets shown in Figure 13.The above given association rules revealed the pairs of item groups, from which different items sold together.

```
=== Run information ===

Scheme:       weka.associations.FPGrowth -P 2 -I -1 -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1
Relation:     Supermarketv1_winter_1
Instances:    8
Attributes:   7
              TEA
              BISCUIT
              SOAP
              DETERGENT
              SHAMPOO
              SUGAR
              MILK
=== Associator model (full training set) ===

FPGrowth found 11 rules (displaying top 10)

 1. [BISCUIT=1]: 3 ==> [TEA=1]: 3   <conf:(1)> lift:(2) lev:(0.19) conv:(1.5)
 2. [SUGAR=1]: 1 ==> [TEA=1]: 1   <conf:(1)> lift:(2) lev:(0.06) conv:(0.5)
 3. [MILK=1]: 1 ==> [TEA=1]: 1   <conf:(1)> lift:(2) lev:(0.06) conv:(0.5)
 4. [SHAMPOO=1]: 1 ==> [SOAP=1]: 1   <conf:(1)> lift:(4) lev:(0.09) conv:(0.75)
 5. [SUGAR=1]: 1 ==> [MILK=1]: 1   <conf:(1)> lift:(8) lev:(0.11) conv:(0.88)
 6. [MILK=1]: 1 ==> [SUGAR=1]: 1   <conf:(1)> lift:(8) lev:(0.11) conv:(0.88)
 7. [SUGAR=1]: 1 ==> [TEA=1, MILK=1]: 1   <conf:(1)> lift:(8) lev:(0.11) conv:(0.88)
 8. [TEA=1, SUGAR=1]: 1 ==> [MILK=1]: 1   <conf:(1)> lift:(8) lev:(0.11) conv:(0.88)
 9. [MILK=1]: 1 ==> [TEA=1, SUGAR=1]: 1   <conf:(1)> lift:(8) lev:(0.11) conv:(0.88)
10. [TEA=1, MILK=1]: 1 ==> [SUGAR=1]: 1   <conf:(1)> lift:(8) lev:(0.11) conv:(0.88)
```

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```
=== Run information ===

Scheme:       weka.associations.FPGrowth -P 2 -I -1 -N 8 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1
Relation:     Supermarketv1_summer_1
Instances:    7
Attributes:   10
              SHAMPOO
              SOAP
              BUTTER
              BREAD
              CHEESE
              AGARBATI
              MATCHBOX
              SOFTDRINK
              CHIPS
              BISCUIT
=== Associator model (full training set) ===

FPGrowth found 12 rules (displaying top 8)

1. [SOFTDRINK=1]: 3 ==> [CHIPS=1]: 3   <conf:(1)> lift:(2.33) lev:(0.24) conv:(1.71)
2. [CHIPS=1]: 3 ==> [SOFTDRINK=1]: 3   <conf:(1)> lift:(2.33) lev:(0.24) conv:(1.71)
3. [SOFTDRINK=1]: 3 ==> [BISCUIT=1]: 3   <conf:(1)> lift:(2.33) lev:(0.24) conv:(1.71)
4. [BISCUIT=1]: 3 ==> [SOFTDRINK=1]: 3   <conf:(1)> lift:(2.33) lev:(0.24) conv:(1.71)
5. [CHIPS=1]: 3 ==> [BISCUIT=1]: 3   <conf:(1)> lift:(2.33) lev:(0.24) conv:(1.71)
6. [BISCUIT=1]: 3 ==> [CHIPS=1]: 3   <conf:(1)> lift:(2.33) lev:(0.24) conv:(1.71)
7. [SOFTDRINK=1]: 3 ==> [CHIPS=1, BISCUIT=1]: 3   <conf:(1)> lift:(2.33) lev:(0.24) conv:(1.71)
8. [CHIPS=1]: 3 ==> [SOFTDRINK=1, BISCUIT=1]: 3   <conf:(1)> lift:(2.33) lev:(0.24) conv:(1.71)
```

```
=== Run information ===

Scheme:       weka.associations.FPGrowth -P 2 -I -1 -N 8 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1
Relation:     Supermarketv1_monsoon_1
Instances:    9
Attributes:   8
              SHAMPOO
              SOAP
              TEA
              BISCUIT
              AGARBATI
              MATCHBOX
              CHIPS
              SOFTDRINK
=== Associator model (full training set) ===

FPGrowth found 4 rules (displaying top 4)

1. [SOAP=1]: 2 ==> [SHAMPOO=1]: 2   <conf:(1)> lift:(2.25) lev:(0.12) conv:(1.11)
2. [CHIPS=1]: 1 ==> [TEA=1]: 1   <conf:(1)> lift:(4.5) lev:(0.09) conv:(0.78)
3. [MATCHBOX=1]: 2 ==> [AGARBATI=1]: 2   <conf:(1)> lift:(4.5) lev:(0.17) conv:(1.56)
4. [AGARBATI=1]: 2 ==> [MATCHBOX=1]: 2   <conf:(1)> lift:(4.5) lev:(0.17) conv:(1.56)
```

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```
=== Run information ===

Scheme:       weka.associations.FPGrowth -P 2 -I -1 -N 10 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1
Relation:     Supermarketv2_winter_2
Instances:    8
Attributes:   8
              COFFEE
              BISCUIT
              TEA
              SHAMPOO
              KETCHUP
              BREAD
              JAM
              MILK
=== Associator model (full training set) ===

FPGrowth found 6 rules (displaying top 6)

1. [KETCHUP=1]: 3 ==> [COFFEE=1]: 3   <conf:(1)> lift:(1.33) lev:(0.09) conv:(0.75)
2. [SHAMPOO=1]: 1 ==> [COFFEE=1]: 1   <conf:(1)> lift:(1.33) lev:(0.03) conv:(0.25)
3. [SHAMPOO=1]: 1 ==> [TEA=1]: 1   <conf:(1)> lift:(2.67) lev:(0.08) conv:(0.63)
4. [SHAMPOO=1]: 1 ==> [COFFEE=1, TEA=1]: 1   <conf:(1)> lift:(4) lev:(0.09) conv:(0.75)
5. [COFFEE=1, SHAMPOO=1]: 1 ==> [TEA=1]: 1   <conf:(1)> lift:(2.67) lev:(0.08) conv:(0.63)
6. [TEA=1, SHAMPOO=1]: 1 ==> [COFFEE=1]: 1   <conf:(1)> lift:(1.33) lev:(0.03) conv:(0.25)
```

```
=== Run information ===

Scheme:       weka.associations.FPGrowth -P 2 -I -1 -N 8 -T 0 -C 0.9 -D 0.05 -U 1.0 -M 0.1
Relation:     Supermarketv2_summer_2
Instances:    8
Attributes:   10
              SOFTDRINK
              MILKSHAKE
              SHAMPOO
              BREAD
              BUTTER
              JUICE
              SOAP
              TEA
              AGARBATI
              SUGAR
=== Associator model (full training set) ===

FPGrowth found 14 rules (displaying top 8)

1. [SOFTDRINK=1]: 3 ==> [JUICE=1]: 3   <conf:(1)> lift:(2.67) lev:(0.23) conv:(1.88)
2. [JUICE=1]: 3 ==> [SOFTDRINK=1]: 3   <conf:(1)> lift:(2.67) lev:(0.23) conv:(1.88)
3. [SUGAR=1]: 1 ==> [BREAD=1]: 1   <conf:(1)> lift:(4) lev:(0.09) conv:(0.75)
4. [MILKSHAKE=1]: 1 ==> [BREAD=1]: 1   <conf:(1)> lift:(4) lev:(0.09) conv:(0.75)
5. [BUTTER=1]: 1 ==> [BREAD=1]: 1   <conf:(1)> lift:(4) lev:(0.09) conv:(0.75)
6. [TEA=1]: 1 ==> [SOAP=1]: 1   <conf:(1)> lift:(8) lev:(0.11) conv:(0.88)
7. [SOAP=1]: 1 ==> [TEA=1]: 1   <conf:(1)> lift:(8) lev:(0.11) conv:(0.88)
8. [SUGAR=1]: 1 ==> [MILKSHAKE=1]: 1   <conf:(1)> lift:(8) lev:(0.11) conv:(0.88)
```

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```
=== Run information ===

Scheme:       weka.associations.FPGrowth -P 2 -I -1 -N 8 -T 0 -C 0.67 -D 0.05 -U 1.0 -M 0.1
Relation:     Supermarketv3_winter_3
Instances:    9
Attributes:   9
              SOUP
              BREAD
              KETCHUP
              SOAP
              DETERGENT
              SHAMPOO
              BISCUIT
              COFFEE
              JUICE
=== Associator model (full training set) ===

FPGrowth found 18 rules (displaying top 8)

1. [COFFEE=1]: 4 ==> [BISCUIT=1]: 4   <conf:(1)> lift:(2.25) lev:(0.25) conv:(2.22)
2. [BISCUIT=1]: 4 ==> [COFFEE=1]: 4   <conf:(1)> lift:(2.25) lev:(0.25) conv:(2.22)
3. [JUICE=1]: 1 ==> [COFFEE=1]: 1   <conf:(1)> lift:(2.25) lev:(0.06) conv:(0.56)
4. [JUICE=1]: 1 ==> [BISCUIT=1]: 1   <conf:(1)> lift:(2.25) lev:(0.06) conv:(0.56)
5. [SOUP=1]: 2 ==> [BREAD=1]: 2   <conf:(1)> lift:(3) lev:(0.15) conv:(1.33)
6. [KETCHUP=1]: 1 ==> [BREAD=1]: 1   <conf:(1)> lift:(3) lev:(0.07) conv:(0.67)
7. [SOAP=1]: 1 ==> [DETERGENT=1]: 1   <conf:(1)> lift:(4.5) lev:(0.09) conv:(0.78)
8. [SHAMPOO=1]: 1 ==> [DETERGENT=1]: 1   <conf:(1)> lift:(4.5) lev:(0.09) conv:(0.78)
```

```
=== Run information ===

Scheme:       weka.associations.FPGrowth -P 2 -I -1 -N 8 -T 0 -C 0.67 -D 0.05 -U 1.0 -M 0.1
Relation:     Supermarketv4_winter4
Instances:    10
Attributes:   9
              TEA
              BISCUIT
              SOUP
              BREAD
              SOAP
              SHAMPOO
              KETCHUP
              AGARBATI
              DETERGENT
=== Associator model (full training set) ===

FPGrowth found 5 rules (displaying top 5)

1. [BISCUIT=1]: 2 ==> [TEA=1]: 2   <conf:(1)> lift:(2.5) lev:(0.12) conv:(1.2)
2. [SOUP=1]: 2 ==> [BREAD=1]: 2   <conf:(1)> lift:(5) lev:(0.16) conv:(1.6)
3. [BREAD=1]: 2 ==> [SOUP=1]: 2   <conf:(1)> lift:(5) lev:(0.16) conv:(1.6)
4. [SHAMPOO=1]: 1 ==> [SOAP=1]: 1   <conf:(1)> lift:(5) lev:(0.08) conv:(0.8)
5. [DETERGENT=1]: 1 ==> [SOAP=1]: 1   <conf:(1)> lift:(5) lev:(0.08) conv:(0.8)
```

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```
=== Run information ===

Scheme:       weka.associations.FPGrowth -P 2 -I -1 -N 8 -T 0 -C 0.67 -D 0.05 -U 1.0 -M 0.1
Relation:     Supermarketv5_winter5
Instances:    9
Attributes:   10
              INSTANT_NOODLES
              CHIPS
              COFFEE
              BREAD
              MILK
              AGARBATI
              MIXED_SPICES
              TEA
              BISCUIT
              SHAMPOO
=== Associator model (full training set) ===

FPGrowth found 6 rules (displaying top 6)

1. [TEA=1]: 2 ==> [MIXED_SPICES=1]: 2   <conf:(1)> lift:(4.5) lev:(0.17) conv:(1.56)
2. [MIXED_SPICES=1]: 2 ==> [TEA=1]: 2   <conf:(1)> lift:(4.5) lev:(0.17) conv:(1.56)
3. [CHIPS=1]: 1 ==> [INSTANT_NOODLES=1]: 1   <conf:(1)> lift:(4.5) lev:(0.09) conv:(0.78)
4. [BISCUIT=1]: 1 ==> [COFFEE=1]: 1   <conf:(1)> lift:(4.5) lev:(0.09) conv:(0.78)
5. [MILK=1]: 1 ==> [BREAD=1]: 1   <conf:(1)> lift:(4.5) lev:(0.09) conv:(0.78)
6. [SHAMPOO=1]: 1 ==> [AGARBATI=1]: 1   <conf:(1)> lift:(4.5) lev:(0.09) conv:(0.78)
```

Figure 13: Association Rules of Five Supermarkets

6. Comparative Study Of Five Supermarkets

The Comparative Study of Five Supermarkets has been done to give knowledge to the retailer about the highest and least sold items among all the five supermarkets for the seasons Winter, Summer and Monsoon. First, the data is extracted from the bar charts of every supermarket using Java and is stored in MySQL database. The highest and least sold items in a particular season for each of the five supermarkets have then been found and displayed using MySQL database. Figure 14 displays the highest and lowest items in every season for each of the five supermarkets. Then the overall highest and lowest occurring item is then calculated among all the five supermarkets. For example, it has been found that Tea is the highest sold item and Shampoo is the least sold item in all the five supermarkets during the winter season. Similarly, the highest and lowest sold items are found for every season among all supermarkets. Figure 15 displays the highest and lowest sold items across all five supermarkets in graphical form using Power BI.

Don't Limit
Result Grid | Filter Rows: | Export: | Wrap Cell Content:

supermarket_name	season	High	Low
Supermarket1	Winter	Tea	Shampoo
Supermarket1	Summer	Softdrink	Butter
Supermarket1	Monsoon	Shampoo	Softdrink
Supermarket2	Winter	Tea	Shampoo
Supermarket2	Summer	Softdrink	Butter
Supermarket2	Monsoon	Toothpaste	Biscuit
Supermarket3	Winter	Soup	Shampoo
Supermarket3	Summer	Milkshake	Coffee
Supermarket3	Monsoon	Shampoo	Detergent
Supermarket4	Winter	Tea	Shampoo
Supermarket4	Summer	Icecream	Chips
Supermarket4	Monsoon	Shampoo	Hot_Cho...
Supermarket5	Winter	Mixed_Spices	Shampoo
Supermarket5	Summer	Icecream	Butter
Supermarket5	Monsoon	Instant_N...	Detergent

Figure 14: Highest and Lowest Sold Items in Every Supermarket In Every Season

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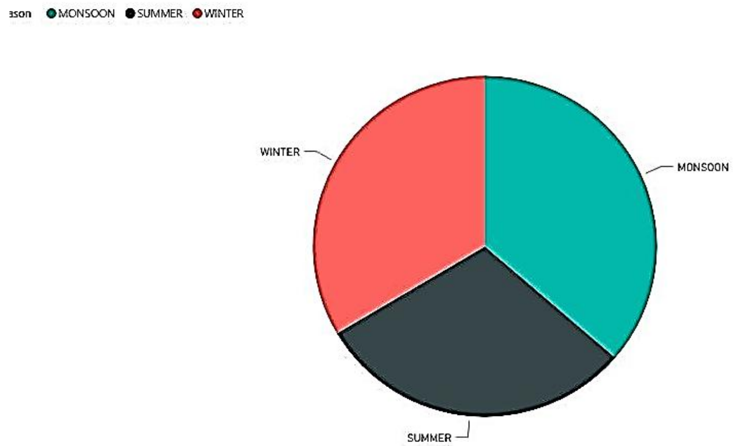

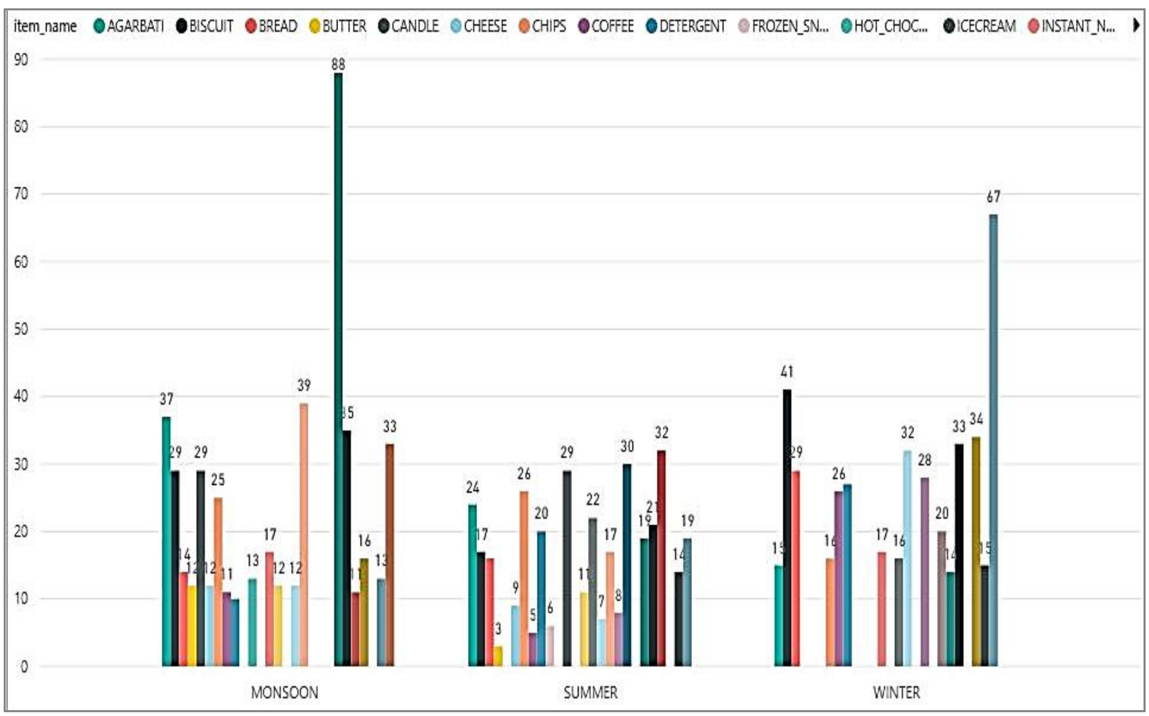

Figure 15: Highest and Lowest Sold Items in Every Supermarket in Every Season in Graphical Form using Power BI

7. Conclusion

In this research paper, two major algorithms J48 decision tree algorithm for classification and FP-Growth for finding association rules have been used to mine the large transactional retail data set. Both the algorithms generated hidden facts regarding the retail transactional data set, which help the retailer to design the store layout according to the correlated and most frequent item groups. The retailer can also plan the schemes, promotional offers or sale according to the analysis. The comparative study of five supermarkets helps the retailer in gaining knowledge about the highest and lowest sold item in a particular season across five supermarkets. This analysis is helpful for increasing the sale of items and generating more profit and customer preferences of a particular product in a particular season.

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