Abstract:

The aim of the research is to discuss forms of measurement and analytics which serve to achieve an expanding footprint for online marketplace "Trice". Companies are increasingly using online communities to create value for the firm and their customers. To date, evidence regarding the effectiveness of online communities is widely available. In this paper we carry out a detailed study with live data from the business. The study is underpinned by a Sample survey of varied individuals, Sample size- 199. Further there is a detailed study carried out for Market basket analysis, RFM, LTV. The result is an outcome of amalgamated concurrence of survey and Statistical analysis. The results show there is strong traction for the brand and awareness in the market it is operating. The study points to few important outcomes, Namely: There is a strong loyal customer base, which brings in business and profits. In recent years , especially after the event of COVID 19, the traction of the business has slowed down and the latest customer acquisition by expanded marketing is not revenue accretive. The survey provides insight on the latest preferences of the customers and their areas of interest, which should be further taken up by the "Trice"marketing team. The study proposes to the company in starting a "loyalty program" which will lead to customer retention thereby assisting in getting more cross-sell and upsell opportunities.

Key words: Association rule mining, Apriori Algorithm, Market Basket Analysis, Big Data, Quantitative survey, RFM Analysis, Customer LTV, Neighbourhood app

Introduction:

"Trice" is an online neighbourhood marketplace which is based on the simple principle of creating a connected community. Trice helps build thriving and active residential communities by promoting local commerce in helping like-minded people. The app creates a positive social impact empowering women, creating local employment thereby stimulating the local economy.

Trice operates in a constantly changing environment, which uses sophisticated tools and new approaches to understand customer journeys.

"Trice" currently has strong patronage with the local community they work in and has several "Marquee investors". "Trice" wishes to expand its footprint and hence this research study is commissioned.

Further details about the business can be found in https://www.tricecommunity.com/tc#/home

Business Problem:

The app "Trice" has strong patronage, still the project team would like more traction for the app to expand the business further to bring in more customers and profit.

Business Gap:

To identify business case studies and research papers in relation to online marketplace connecting neighbourhoods for mutual benefit and the existing analysis and literature.

Research problem/Problem Statement:

To Identify few outcomes/suggestions for the business development through study of live data through “Statistical analysis”

Literature Review:

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Research Methodology:

The data collected is placed under different criteria to get the objective.

Data Collection:

As part of the assignment process we have approached Trice Systems Pvt Ltd Company and used there live data to analyse and see how we can use statistical methods to infer as to what is happening and how they can improve their customer experience

As part of data collection we have collected the below data and the reason for the same is explained as below

Customer Master:

Order ID: This is the unique table that records each order and ties it to the respective customer to analyse patterns and behavior, this table is unique and cannot have duplicates

User ID: This is the table the uniquely identifies each customer and helps identify what all he transacted and where all did he travel along in the app, what are his favourite things on the store, what are his demographics, what he orders and dosent order

Order Date: Helps us in identifying a pattern as to the frequency of his purchase, is he a monthly purchases, weekly or daily, helps in targeting promotion before his next purchase cycle

Order Type: This helps in identifying what is his favourite type on the app, Store orders, Food orders, subscription orders etc, this helps in identifying if he is a food lover or a planned purchaser etc

Store: Which vendor store the customer likes, this is based on the frequency of his purchase which we can capture using the data available in the above tables to triangulate his choice and preference

Service / Category: This helps in identifying at a service level what customer he is, a meat lover, vegetarian, foodie, gamer etc

Bill Amount: This field helps in identifying what is the bill amount and when taken in conjunction with order frequency gives us avg order value, avg cart value, service wise bill value etc

Order Master

Order ID: This is the critical link that connects the customer table in relation with order table as the unique common factor and identifier, without this link the entire data becomes useless since we cannot establish the relation between both the tables

Payment ID: This table identifies how the payment came in, what mode customer used, what are his preferred usage mode, like Card, Net Banking, UPI, COD, etc and based on this learning we can offer him any promotions as and when they come

Store Name: Which vendor store the customer likes, this is based on the frequency of his purchase which we can capture using the data available in the above tables to triangulate his choice and preference

Product Name: This table identifies the name of the product that the customer bought and analyzing this we can get his preferred product that he buys frequently, in conjunction with other info we can arrive at the frequency bought, regularity etc.

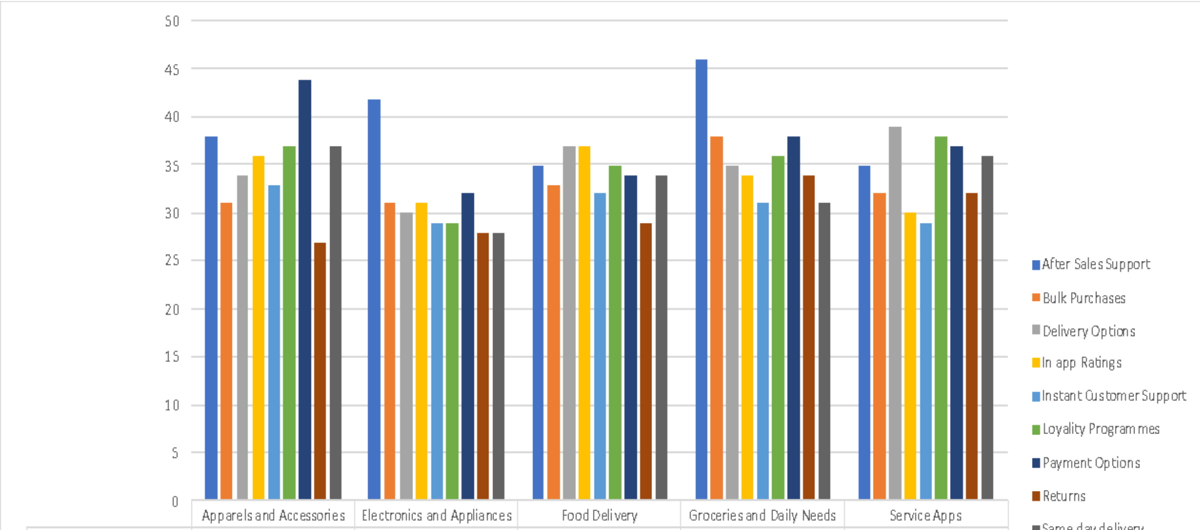
Survey

A detailed Survey is conducted with existing and new customers to understand their motivation for using the product and expand the footprint. The survey also detailed the areas of comfort and pain points. We designed the questionnaire and it was released in various social media channels (whatsapp groups, emails to existing clients) through formstack. The questionnaire was released on Oct 14 to 26. The responses are collected and analyzed deeper for business insights.

The model Questionnaire is attached to this paper for easy reference

The salient survey insights are as follows.

SERVICE VS FEATURES:

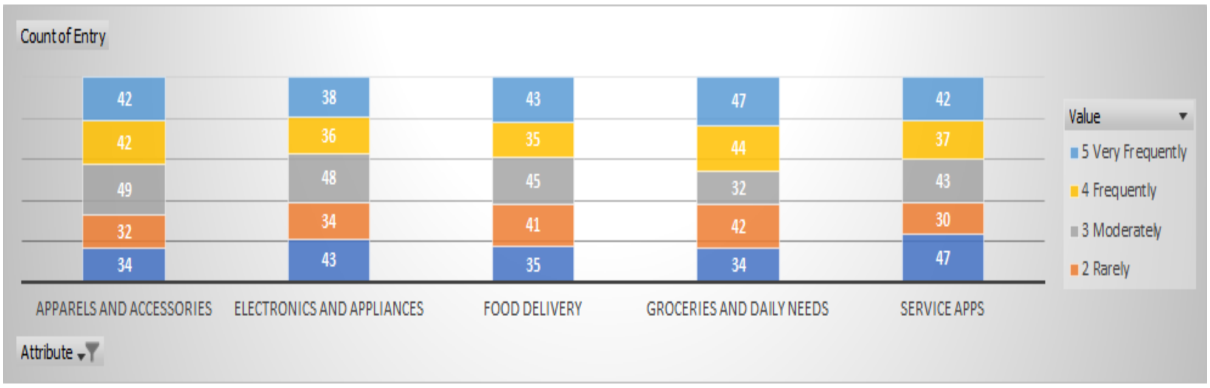


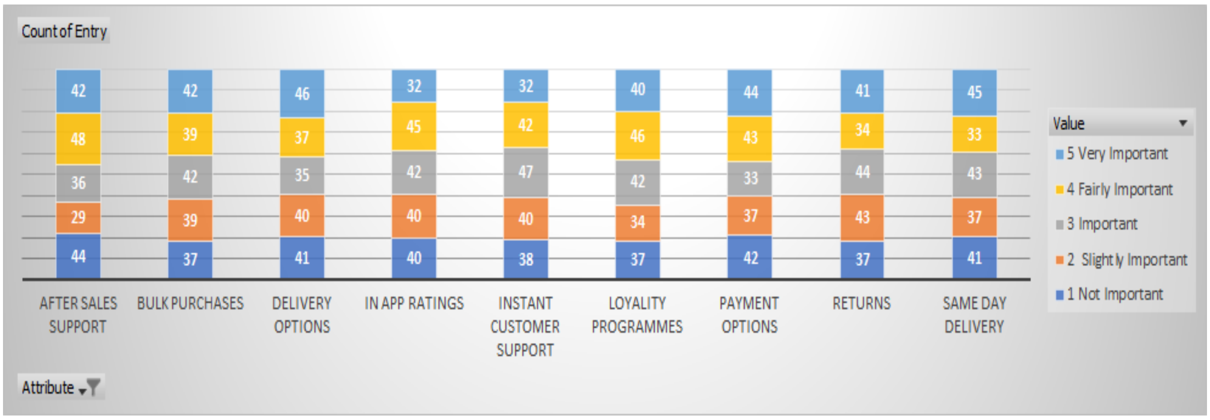
	Apparels and Accessories	Electronics and Appliances	Food Delivery	Groceries and Daily Needs	Service Apps
After Sales Support	38	42	35	46	35
Bulk Purchases	31	31	33	38	32
Delivery Options	34	30	37	35	39
In app Ratings	36	31	37	34	30
Instant Customer Support	33	29	32	31	29
Loyality Programmes	37	29	35	36	38
Payment Options	44	32	34	38	37
Returns	27	28	29	34	32
Same day delivery	37	28	34	31	36

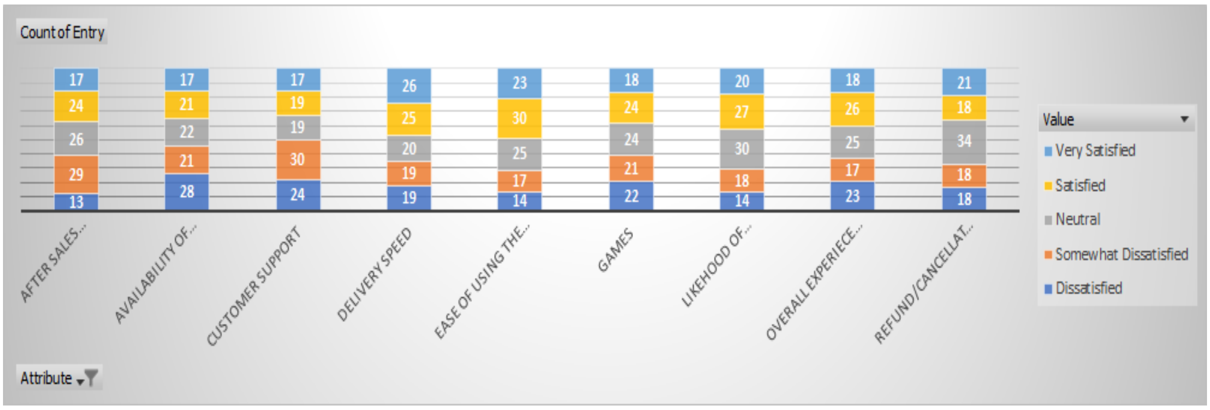
As per the above graph

- Customers who prefer apparel and accessories frequently have strong preference for various payment options and ease of use.
- For Customers who prefer electronics, groceries and daily needs their priority was after sales support.
- For customers who prefer Apparels and accessories, Service apps, have strong preference to same day delivery.
- The above outcomes can be linked with Market basket analysis, RFM and LTV models generated in more ways to gain deeper understanding

Overall survey report



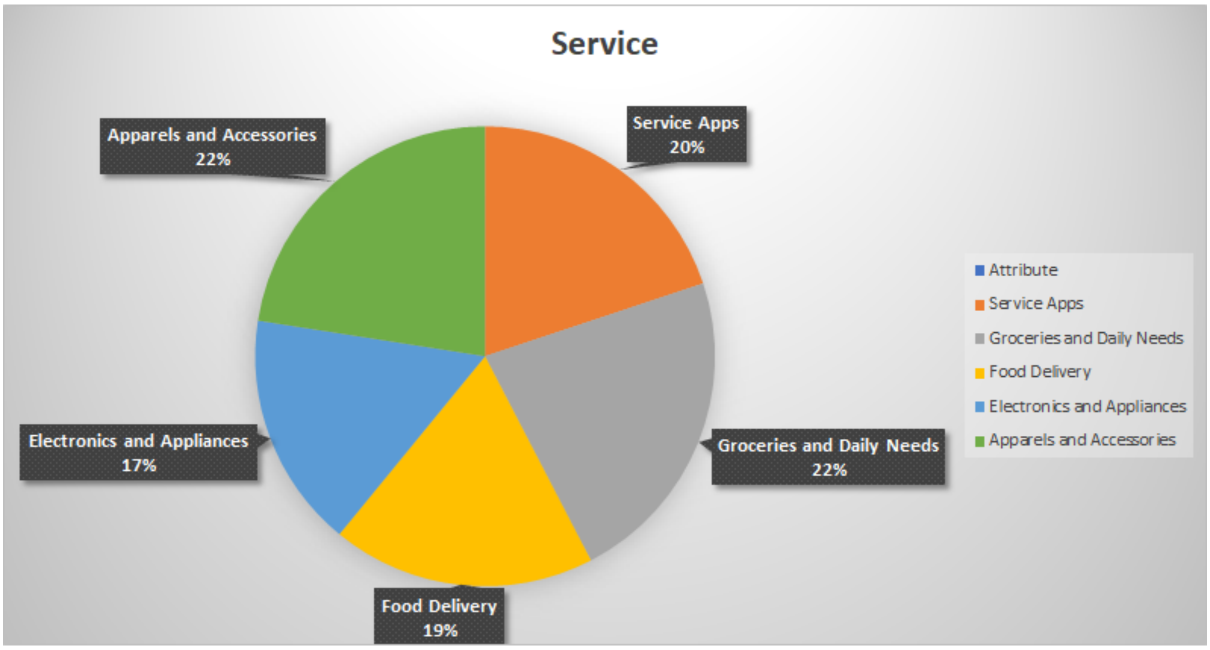


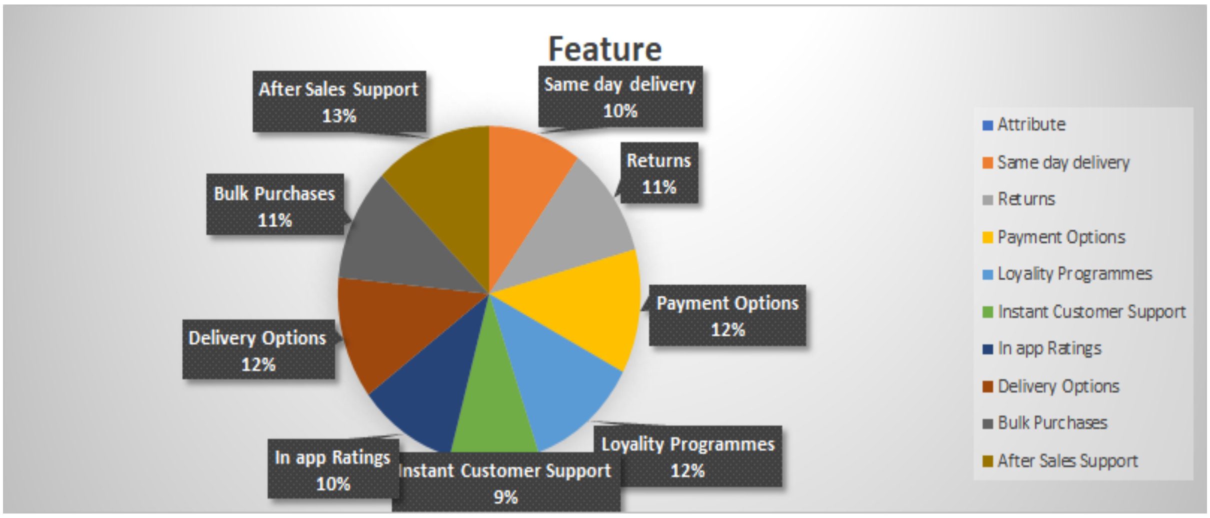


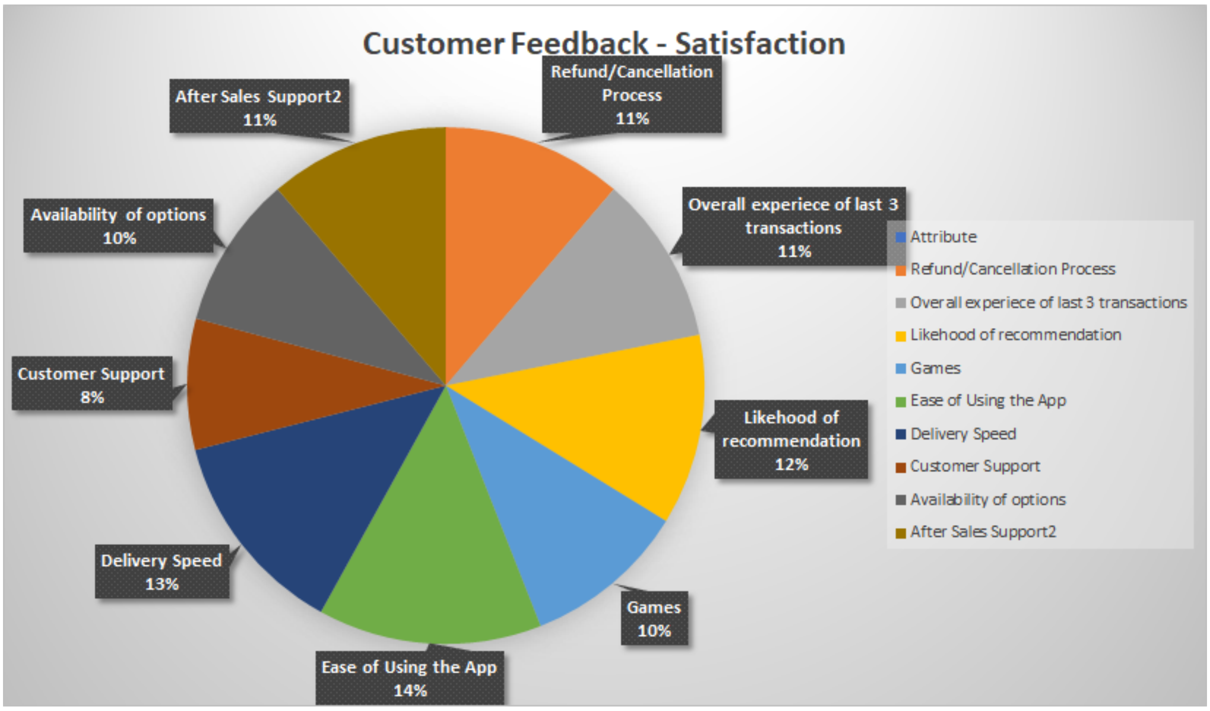
- The outliers (i.e Age 16-20 & 65 +) use more service apps than any other apps and they are mostly interested in loyalty programs and freebies than that of any other services.

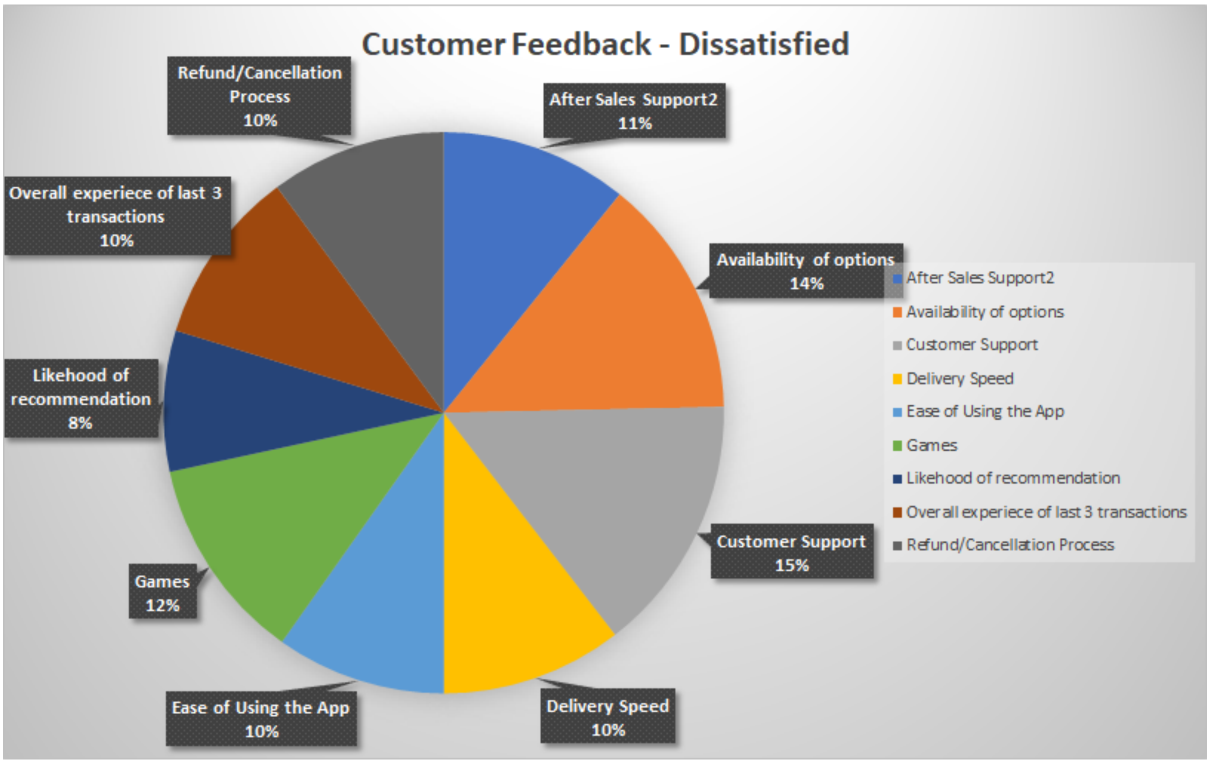
- Groceries and food delivery are used more frequently than any other app services which makes us understand that there is more demand for these apps and this phenomenon was observed across all age spectrums.
- Delivery options and same day delivery is more preferred by our customers and the least being bulk purchases and payment options
- The existing customers are very satisfied with the current refund/ refunds policies and there are some challenges in options availability and customer support

Pie support on importance and dissatisfaction of existing customers




Feature
After Sales Support 13%
Same day delivery 10%
Returns 11%
Bulk Purchases 11%
Payment Options 12%
Delivery Options 12%
In app Ratings 10%
Instant Customer Support 9%
Loyality Programmes 12%
Attribute
Same day delivery
Returns
Payment Options
Loyality Programmes
Instant Customer Support
In app Ratings
Delivery Options
Bulk Purchases
After Sales Support


Customer Feedback - Satisfaction
After Sales Support2 11%
Refund/Cancellation Process 11%
Availability of options 10%
Overall experiece of last 3 transactions 11%
Customer Support 8%
Likehood of recommendation 12%
Delivery Speed 13%
Games 10%
Ease of Using the App 14%
Attribute
Refund/Cancellation Process
Overall experiece of last 3 transactions
Likehood of recommendation
Games
Ease of Using the App
Delivery Speed
Customer Support
Availability of options
After Sales Support2



- in service apps the frequently used one is Groceries and Daily Needs and infrequent is Electronics and Appliances
- 66 people felt payment option is more important feature than any other feature
- The most satisfaction came from the ease of using app and we need to focus more on customer support as we got very less support in our survey
- The Highest amount of dissatisfaction is from customer support and definitely needs some improvement
- Also need more focus on the likelihood of recommendation as it is again dependant on the overall service

Market Basket Analysis

Data mining refers to extracting knowledge from a large amount of data. Market basket analysis is a data mining technique to discover associations between datasets. Association rule mining identifies relationships between a large set of data items. When large quantities of data are constantly obtained and stored in databases, several industries are becoming concerned about mining association rules from their databases. For example, the detection of interesting association relationships between large quantities of business transaction data can help in catalog design, cross-marketing and various business decision making processes. A typical example of association rule mining is market basket analysis. This method examines customer buying patterns by identifying associations among various items that customers place in their shopping baskets. The identification of such associations can assist retailers expand marketing strategies by gaining insight into which items are frequently purchased by customers. It is helpful to examine the customer purchasing behavior and assists in increasing the sales

Market Basket Analysis is used for mining frequent itemsets and relevant association rules. It is devised to operate on a database containing a lot of transactions.

Association rules are normally written like this: {Diapers} -> {Beer} which means that there is a strong relationship between customers that purchased diapers and also purchased beer in the same transaction.

In the above example, the {Diaper} is the **antecedent** and the {Beer} is the **consequent**. Both antecedents and consequent can have multiple items. In other words, {Diaper, Gum} -> {Beer, Chips} is a valid rule.

Support is an indication of how frequently the itemset appears in the dataset. The support of X with respect to T is defined as the proportion of transactions t in the dataset which contains the itemset X.

$$\text{Support}(A \rightarrow C) = \text{support}(A \cup C), \text{range: } [0,1]$$

Confidence is an indication of how often the rule has been found to be true. The confidence value of a rule, X=>Y , with respect to a set of transactions T, is the proportion of the transactions that contain X which also contain Y.

$$\text{Confidence}(A \rightarrow C) = \text{support}(A \rightarrow C)/\text{support}(A), \text{range: } [0,1]$$

Lift is the ratio of the observed support to that expected if the two rules were independent . The basic rule of thumb is that a lift value close to 1 means the rules were completely independent. Lift values > 1 are generally more "interesting" and could be indicative of a useful rule pattern.

$$\text{lift}(A \rightarrow C) = \text{confidence}(A \rightarrow C)/\text{support}(C), \text{range: } [0,\infty]$$

The Data Set:

The data set we used is "TriceMBA.csv".It has 3 fields-UID(User ID), Service, Count(quantity of items)

Variable	Description	Data Type

UID	User ID of the customer	Int
Service	Availed services to the customer from Trice	String
Count	Number of times user ordered the service	Int

Cleaning the data set:-

We got a raw data set "sale dump 36 months with cust ID.xlsx" from trice and we removed the rows with null values. We took the field "Service" to find out the frequent patterns instead of the item field because the items are of high dimensional and they are nearly 23410 unique items. As Trice is a service based application, we thought it would be more reasonable to choose the field "service" to find the association between services offered by Trice.

Code:-

Mlxtend (machine learning extensions) is a Python library of useful tools for day-to-day data science tasks.

To install mlxtend, just execute

pip install mlxtend
import mlxtend

Importing apriori and frequent patterns

Apriori function and association rules to extract frequent itemsets for association rule mining.

```
pip install efficient-apriori
pip install apyori
import apyori
from mlxtend.frequent_patterns import apriori, association_rules
```

Numpy provides a high-performance multidimensional array and basic tools to compute with and manipulate these arrays

```
import numpy as np
```

Pandas is a library of python used for data manipulation and analysis.

```
import pandas as pd
```

Downloading the dataset directly from Google Drive via Google Colab

```
from google.colab import drive
drive.mount ('/drive')
data = pd.read_csv('/drive/MyDrive/TriceMBA.csv')
```

The head() function is used to get the first n rows.

```
data.head()
```

```
basket_hot = (data
        .groupby(['UID', 'Service'])['Count']
        .sum().unstack().reset_index().fillna(0)
        .set_index('UID'))
```

One-hot encoding is essentially the representation of categorical variables as binary vectors. These categorical values are first mapped to integer values. Each integer value is then represented as a binary vector that is all 0s (except the index of the integer which is marked as 1).

```
def hot_encode(x):
    if(x<= 0):
        return 0
    if(x>= 1):
        return 1
```

This Pandas function application is used to apply a function to DataFrame, that accepts and returns only one scalar value to every element of the DataFrame.

Defining the hot encoding function to make the data suitable for the concerned libraries

```
basket_encoded = basket_hot.applymap(hot_encode)
basket_hot = basket_encoded
basket_hot
```

We have taken a support count level at 15%

```
frq_items = apriori(basket_hot, min_support = 0.15, use_colnames = True)
frq_items
```

Pandas has a set option function that lets you customize some aspects of its behavior.

```
pd.set_option('display.max_columns', 10)
```

Building the models and analyzing the results

```
rules = association_rules(frq_items, metric ="lift", min_threshold = 1)
rules = rules.sort_values(['confidence', 'lift'], ascending =[False, False])
print(rules.head())
rules.to_excel('/drive/MyDrive/MBA_output.xlsx')
```

Market Basket Analysis Inference:

From the data we have, we observed 42 frequent pattern sets. Through support count, we observed that the percentage of orders are more for services- Fruits & Vegetables, Groceries, Sweets & Namkeens and Bread & Cakes.

Antecedents	Consequents	Support
({'Sweets & Namkeen'})	({'Fruits & Vegetables'})	0.313119436
({'Fruits & Vegetables'})	({'Sweets & Namkeen'})	0.313119436
({'Groceries'})	({'Fruits & Vegetables'})	0.247942214
({'Fruits & Vegetables'})	({'Groceries'})	0.247942214
({'Breads & Cakes'})	({'Fruits & Vegetables'})	0.234839577
({'Fruits & Vegetables'})	({'Breads & Cakes'})	0.234839577

Confidence is the probability that if a person buys an item A, then he will also buy an item B.

Confidence that if a person buys bread & cakes, groceries, they may also buy fruits and vegetables.Which has a 94% chance of being purchased.

Antecedents	Consequents	Confidence
({'Breads & Cakes', 'Groceries'})	({'Fruits & Vegetables'})	0.942044257

Curries and Rotis are having high lift values compared to other items. Which means that these items are appearing more times in the same order.

If the lift value is greater than 1 indicates that the rule body and the rule head appear more often together than expected, this means that the occurrence of the rule body has a positive effect on the occurrence of the rule head.

Antecedents	Consequents	Lift
{'Curries'}	{‘Roti's’}	3.559426973

Further pairings are in the file for Trice to take action calls on

RFM

Introduction:-

RFM analysis is a marketing technique used to quantitatively rank and group customers based on the recency, frequency and monetary total of their recent transactions to identify the best customers and perform targeted marketing campaigns. The system assigns each customer numerical scores based on these factors to provide an objective analysis. RFM analysis is based on the marketing adage that "80% of your business comes from 20% of your customers."

RFM analysis ranks each customer on the following factors:

- **Recency.** How recent was the customer's last purchase? Customers who recently made a purchase will still have the product on their mind and are more likely to purchase or use the product again. Businesses often measure recency in days. But, depending on the product, they may measure it in years, weeks or even hours.
- **Frequency.** How often did this customer make a purchase in a given period? Customers who purchased once are often more likely to purchase again. Additionally, first time customers may be good targets for follow-up advertising to convert them into more frequent customers.
- **Monetary.** How much money did the customer spend in a given period? Customers who spend a lot of money are more likely to spend money in the future and have a high value to a business. In the case of Trice, instead of total sales of the customer, average sales value was taken to get better segmentation.

Trice RFM Analysis:- Below is the data, which is derived from RFM analysis on TRICE customers with a score of 1 being the highest.

RFM code	Segment	Description	No. of Customers	Value
111	Best Customers	Bought most recently and most often, and spend the most No price incentives, new products, and loyalty programs	273	6,11,76,593
12X 11X	Champions	Bought recently, buy often and spend the most	1577	12,57,85,986
X1X	Loyal Customer	Buy most frequently, Use R and M to further segment	1909	16,01,04,999
XX1	Big Spenders	Market your most expensive products	1872	11,48,11,545
444	Lost Cheap Customers	Last purchased long ago, purchased few, and spent little Don't spend too much trying to re-acquire	277	33,557
44X 33X 43X 44X	Hibernating Customers	Last purchase was long back and low number of orders. May be lost	2558	72,04,060

42X 32X	At Risk	Purchased often but a long time ago. Need to bring them back	805	91,83,931
41X 31X	Can't Lose	Used to purchase frequently but haven't returned for a long time.	372	1,55,69,671
24X 34X	About to Sleep	Below average recency and frequency. Will lose them if not reactivated.	657	9,65,160
22X	Customers Needing Attention	Above average recency, frequency and monetary values. May not have bought very recently though.	591	1,26,85,633
24X	Promising	Recent shoppers, but haven't spent much.	234	2,55,697
14X	Recent Customers	Bought most recently, but not often.	61	54,379
23x 22x 13x 12x	Potential Loyalist	Recent customers with average frequency.	1922	2,72,20,289

Insights:

- Our loyal customers which includes the best customers-1909 brings the business of 16 cr. Trice as a business would intend to retain the 1909 loyal customer base.

- We also noticed 1834 customers who are "At risk","Can't Lose","About to sleep" categories are our major areas to focus as per our research.
- In the recent customer survey conducted we identified that loyalty points are important for customers who are very frequently purchasing apparel and accessories and service app's. The survey helped us identify the customer preferences and was able to relate to the above data.
- The "customers needing attention", "promising" provides a potential business of 1.29 cr and TRICE feels the importance of retaining them with more customer support and optimal discounts.
- "Recent customers" and "potential loyalist" in total has about 1980 customers makes us understand the need of anchoring in our platform.
- "Hibernating customers" needs to be activated by giving more preference for targeted advertisements and helping them understand the need of TRICE for them.
- Further insights can be gained by mapping individual customers to their buying preference and insights gained in market basket analysis.

<u>Code:-</u>

We used Tableau for deriving the above summarized data.

The below images are self explanatory and the calculations are made in tableau to arrive at the above data.

RFM F

```
COUNTD([Order ID])
```

RFM R

```
MIN(DATEDIFF('day',[Order Date],TODAY()))

//counts number of days between today and order date
```

M Code

Results are computed along Table (across).

```
if     RANK_PERCENTILE([RFM M], 'asc') <= 0.25 then 4
elseif RANK_PERCENTILE([RFM M], 'asc') <= 0.50 then 3
elseif RANK_PERCENTILE([RFM M], 'asc') <= 0.75 then 2
elseif RANK_PERCENTILE([RFM M], 'asc') <= 1.0 then 1
end
```

RFM Code

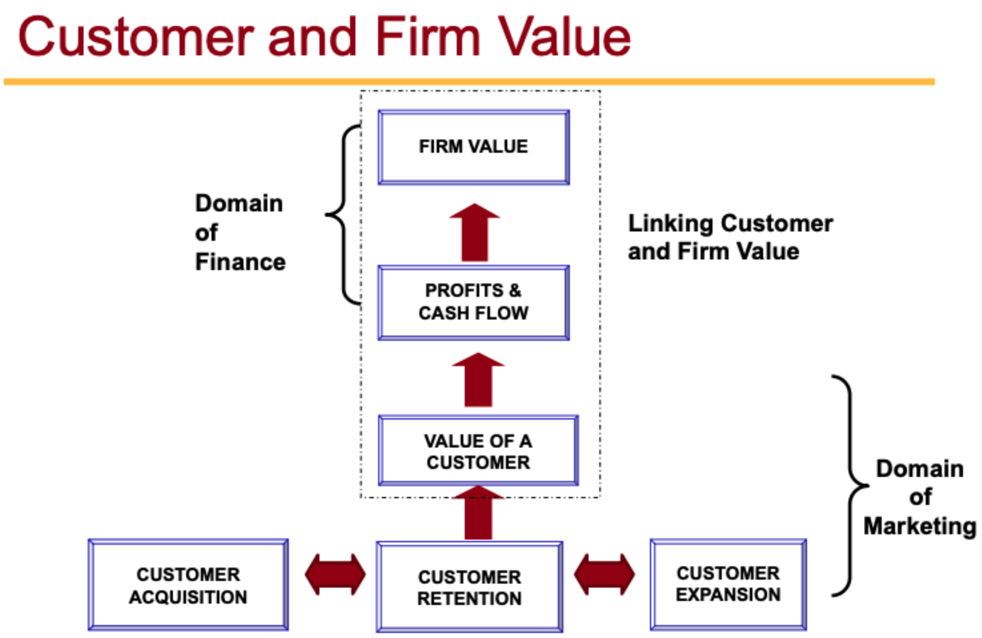
```
[R Code] * 100 + [F Code] * 10 + [M Code]

// To get RFM Code in Same line
```

Lifetime Value(LTV)

Customer Lifetime Value

Customer Lifetime Value is the net present value of all future streams of profits that a customer generates over the life of the relationship with the firm

"Success is getting the right customers … and keeping them," – Charles Cawley,



Founder MBNA

Measuring CLV

CLV = Profit Margin * Margin Multiple – Acquisition Cost

CLV = m{r/(1+i-r)} – AC

Where m = annual margin

r = annual retention rate

i = discount rate

AC = acquisition cost

Margin multiple = r/(1+i-r)

Strategies to increase customer value

1. Customer acquisition

   Customers can be acquired using methods such as

   - Scaling up volume by spending more on existing channels or developing new acquisition channels
   - Improving performance by decreasing cost per acquisition or shifting mix towards high-value customers

2. Customer expansion

   Expansion can be done by various methods that include increase in usage, upsell (switch customers to higher priced product or service), bundling or cross-selling and reducing costs.

   Customer Recommendation Systems

   - Customer Recommender systems are popular in ecommerce and digital content settings.
   - They are useful in context involving a large number of users facing a large number of products
   - There is considerable heterogeneity in user preferences for attributes
   - Users are unaware or uncertain about products
   - Constantly evolving / cold start problems
   - Recommender system algorithms include:
     - Collaborative filtering: this can be User based or Item based
     - Matrix Factorization methods: predicting unknown values using latent factors involves finding the values of the user and item latent factors that minimize the error sum of squares.

3. Customerretention

   Customer Churn is a major impact metric for any organisation. Some of the major causes of churn involve:

   - Company’s poor ongoing customer experience (structural) or a specific incident causes serious customer dissatisfaction (event-based)
   - Competition having promotion (causes switching) and superior value proposition in product or service
   - Customer’s needs change

   Impact of Retention on Market Share

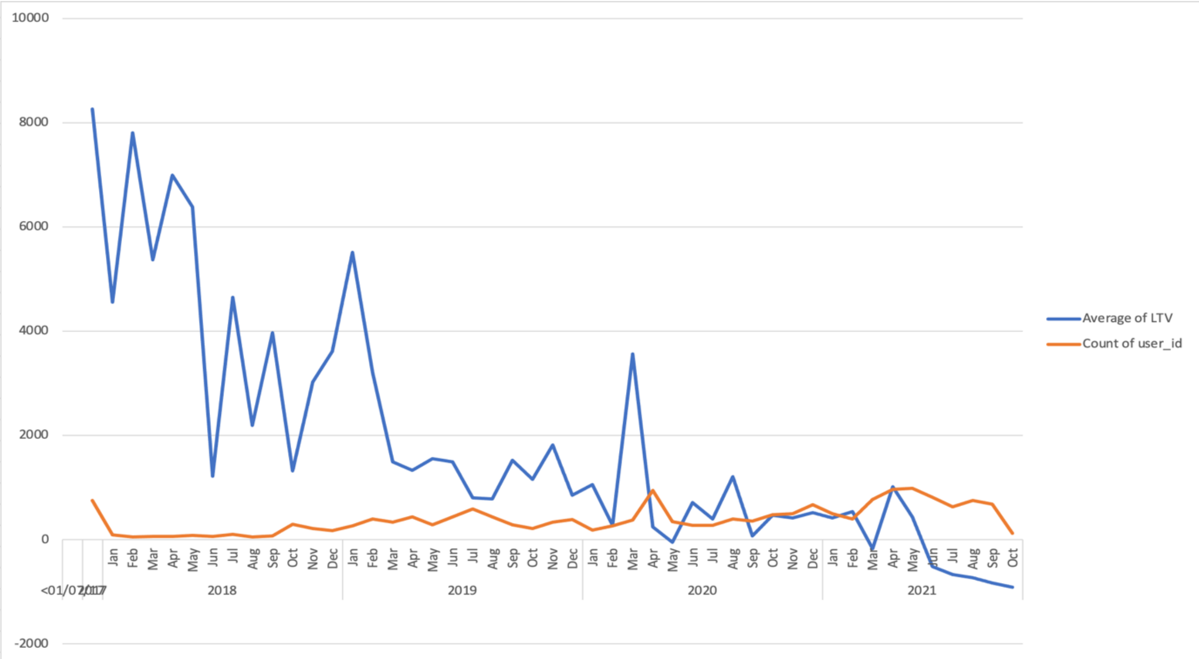
   The 3 drivers of retention and loyalty are:

   - Experience
   - Loyalty Programs
   - Cross-selling

Salient features

- Customers are assets
- Lifetime Value of a customer is $LV = m\,[r/(1+i-r)] - AC$
- Three key levers of growth
  - Customer acquisition (AC)
  - Customer retention (r)
  - Customer expansion (m)

<u>Insights for Trice-CLV:</u>



- Trice has observed a major downfall in customer lifetime value. There is a trend in 2019 where we see a slight decline in LTV, however, due to covid, the decline has continued and Trice has not been able to recover from the impact
- In an effort to recover from this, Trice has pumped in more funds for customer acquisition which did increase their customer base and to some extent their sales numbers, but LTV has been negative since then clearly showing us that acquisition alone isn't an appropriate strategy to recovery.
- Trice will have to concentrate on the other 2 strategies, namely, expansion and retention. They need to improve their retention rate for which they can assess the problem areas and competition, and concurrently focus on creating expansion methods of upselling, cross-selling, recommendation systems to be able to increase their customer LTV

- In 2018, Trice acquired its most valuable customers with minimum spend and maximum LTV, whereas in post covid times, they have burnt funds trying to acquire customers and lost focus on retention.
- The company has only focused on registrations/sign-ups which can be seen from the recent LTV and Revenue per customer data, that majority of these customers have not ordered even once. This depicts another area that needs more focus is to bring in valuable customers that could actually purchase from Trice instead of trying to increase the customer base.
- Loyalty programs paired up with cross-sell and upsell could be a potential best way for Trice to increase their retention rates.
- Incorporating our findings from the survey with the insights gained from the LTV model, we conclude that feature expansion (recommendations, upsell, cross-sell) paired with a loyalty program for customer retention will help Trice recover and thrive. Another example of the need for expansion was the survey response regarding the need for more payment options.
- When it comes to the age group of 16-20 and their interest in freebies, Trice should measure them up against their LTV for that segment and then decide if pumping in more money for them is beneficial at all.

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Results/Conclusion:

The potential for the neighbourhood app “Trice” is substantial from a technical as well as an economical point of view : implying great hitherto untapped business opportunities. The app has a unique business model which is not found in scale across the world . The nearest comparable is “Nextdoor” in the US. One in three US Households are on the platform, hence it is prudent to consider there is abundant scope for “Trice” to grow. The Indian market is always price conscious and this was clearly demonstrated in the survey results and the addition of the new customer base which is not revenue accretive. Through the Market basket analysis it is clear that there is certain correlation between products being sold in the app. Through RFM the research team identified there is a group of customers who are currently on the verge of disconnecting from the app, The “Trice” app team needs to focus on them and retain them. Trice has spent a considerable amount of money for the customer acquisition which has surely increased the customer base but has led to a negative LTV.