Customer Segmentation

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***Abstract*—Customer Segmentation is a way of dividing customers into groups that share similar characteristics. The data-set chosen is extracted from the Machine learning repository. This implementation uses many different approaches to classify customers into other categories-Frequent customers, Infrequent customers, Good customers, low-value customers, high-value customers, champion customers-after preprocessing the extracted data. Analysis of different classifiers used and their pros and cons are presented in this paper. The primary purpose of this analysis is to help the business better understand its customers and therefore conduct customer-centric marketing more effectively.**

***Keywords-segmentation,classification,characteristics,comparing classifiers*.**

I. INTRODUCTION

Not long ago, online retailers focused their marketing efforts around appealing to 'average' customers and attracting as many site visitors to their stores as possible. Customers are more sophisticated in how they navigate their shopping choices, and online retailers are discovering that one-size-fits-all marketing strategies aren't useful anymore In fact targeting the wrong customers can cost you-not just in wasted marketing dollars but in higher operational costs associated with processing product returns, handling customer service calls, and responding to customer reviews. Conversely targeting the right customers can pay you off in terms of higher average order values and increase in profits. Targeting the right customers can also lead to brand advocacy and word-of-mouth advertising, valuable product insights and greater overall customer satisfaction.

One of the biggest challenges with customer segmentation is data quality. Inaccurate data in source systems will usually give low grouping. Data quality issues also arise from lack of maintenance and regular cleaning to ensure accuracy.

Other sections of this paper are organized as follows. Section 2 discusses related work in this field. Section 3 specifies the problem statement and the data-set description. Section 4 discusses the evaluation metrics and how the classifiers were tested. Section 5 shows experiments and results. Finally, Section 6 concludes the paper.

II. LITERATURE SURVEY

In marketing one way to increase profits is to communicate with customers to determine customer wishes[1]. Communication is built according to the characteristics of the customer. Customer segmentation requires customer data from various resources. The data is categorized into internal and external data[2]. Customer registration, customer profile and purchase history are internal data. Census data, media browsing, customer lifestyle are external data. Customer segmentation can be performed using various approaches. Theoretically, Schneider divides customer segmentation methods into geographic, demographic, psychographic[3]. Baer segments customers using business rule method, quantile membership method, supervised clustering with classification and unsupervised clustering using the k-means algorithm[1].

Paper	Method	Data	Advantage	Disadvantage
Magento (2014)	Magento	Demographic, Purchase History, Data Product, Data Media, Data Marketing, Server Log	Have clear variable customer segmentation	There is no data processing for each variable
Baer (2012)	Bussiness Rule	Demographic, Purchase history	Easy to apply, Use database query	Not focus on customer behavior
	Quantile membership	Purchase history	Can process small data, can be used with other data	Good result obtained when determining a good classification
	Supervised Clustering with decision tree	Demographic, Purchase history	Classify customers according to target	Use one variable to cluster
	Unsupervised Clustering	Purchase history	Use any number of customer attributes	Speed of computation depends on k values
Colica (2011)	Customer Profiling	Demographic, Purchase history	use database query if data is small	Not focus on behavior
	Customer Likeness Clustering	Demographic, Purchase History, Data product	classify customers according to the target	Problem arises when there are different unit in record
	RFM Cell Classification Grouping	Purchase history	Efficient three -dimensional mapping	Good result obtained when determining a good classification
	Purchase Affinity Clustering	Purchase history, Data product	know the products most in demand	Spesific to product segmentation

[5] Grouping customers merely based on their expenses may not yield desired outcomes. A model which considers more parameters into consideration is more reliable. One of such methods is the RFM analysis.It scores the customers based on three factors.

- R(recency)
- F(frequency)
- M(monetary)

We can then apply any clustering models such as k-means clustering to segment our customers with similar behaviours detected through RFM scoring.

With the advancement of client oriented behavior in business, developing consideration has been paid to clients and their needs as one of the vital factors to gain higher profit in the industry. Customer relationship management (CRM) looks to distinguish customer needs and encourage collaboration among clients and organizations. With the application of data mining technology in CRM, techniques like decision trees, clustering algorithms, genetic algorithms and association rules in different areas like commerce have been used to solve customer problems and formulate new strategies. Data mining is the statistical analysis of data based on the information of models, which is appropriate for the time period. [4]Recent studies suggest that data changes over time and therefore the results would not be helpful (Roddick and Spiliopoulou, 2002). The present world is in a steady condition of flux that makes the past outcomes outdated. The new methodology is to mine these progressions over time periods. Chen et al (2005) tried to combine customer behavior variables, demographic variables and transaction databases to present a method of mining changes in customer behavior. Böttcher et al (2009) presented a system of customer segmentation based on the discovery of frequent itemsets and the analysis of their change over time. Hu et al (2013) used RFM analysis in the sequential pattern mining process. So, there is a lack of studies on client esteem examination based on clustering techniques.

III. PROBLEM STATEMENT AND DATA-SET DESCRIPTION

Dividing the customers into groups of individuals that are similar in specific ways relevant to marketing, such as age, gender, interests and spending habits. How can we divide customers into groups based on the characteristics they share ? We will discuss various approaches in further sections.
The data-set chosen is taken from the Machine learning repository. The link for the data-set is given below
https://archive.ics.uci.edu/ml/datasets/Online+Retail#

This is the transactional data-set which contains all the transactions occurring between 01/12/2010 and 09/12/2011 for a UK based and non-registered non-store online retail. The data-set consists of 8 attributes.

Attribute information:

- InvoiceNo(Nominal):6-digit integral number uniquely assigned to each transaction.
- StockCode(Nominal):5-digit integral number uniquely assigned to products.
- Description(Nominal):Product name
- Quantity(Numeric):Quantity of each product per transaction.
- InvoiceDate(Ordinal): Timestamp of transaction
- UnitPrice(Numeric):Product price per unit.
- CustomerID(Nominal):5-digit integral number uniquely assigned to each customer.
- Country(Nominal):The name of the country where the customer resides.

IV. ANALYSIS

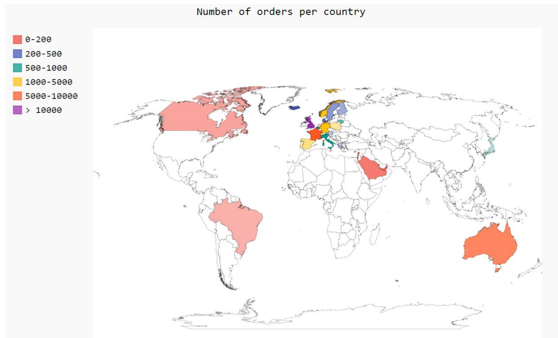
Sales and marketing supervisors need to fragment their clients and information so as to offer leads, openings, and past clients customized encounters that lead to higher transformations and a superior in general customer experience. Every business is different and every customer is different, so one segment will never cover all the aspects. So to overcome this issue we will be combining all the segments - Behavioral, Demographic, Psychographic and Hybrid segments including the cohort analysis and then make clusters according to their RFM scores in order to get better and focused results

Preprocessing

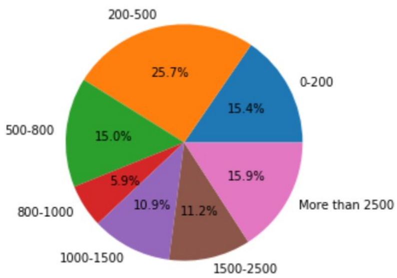
- Missing Values are removed
- Duplicate Values are removed
- There were some negative values observed in the column 'Quantity', which could be due to any of these reasons - it might be purchased and returned product , discount or error. The values which do not have any previous purchase history nor have description as 'Discount' are error values and such rows should be removed from the dataframe.

EDA and Visualisation

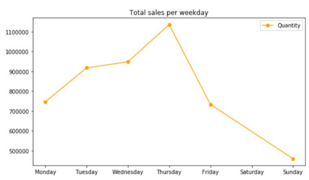
- Dividing the customers based on geographic information.

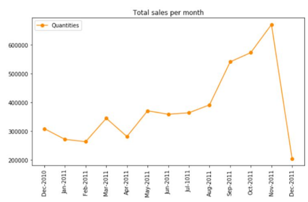


- Customers and their expenses



- Sales(per weekday/per month)





The above visualisations yield interesting insights:

1. Thursday seems to be the day with the highest number of sales.

2. Friday and Sunday have very less sales.
3. The Pre-Christmas season starts in september due to which there's a peak in sales in november
4. February and April have very low sales

V. Proposed Approach

1. Cohort Analysis(Time based cohorts)

Cohort analysis is a tool to quantify customer commitment after some time. It assists with knowing whether customer commitment is really improving after some time or is just seeming to improve as a result of development.

Cohort Value Table:

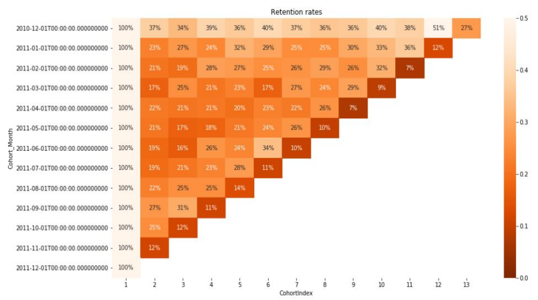
CohortIndex Cohort_Month	1	2	3	4	5	6	7	8	9	10	11	12	13
2010-12-01	885.0	331.0	297.0	344.0	322.0	354.0	328.0	315.0	321.0	351.0	332.0	450.0	243.0
2011-01-01	417.0	96.0	112.0	99.0	134.0	123.0	104.0	104.0	126.0	138.0	152.0	52.0	NaN
2011-02-01	380.0	78.0	74.0	108.0	104.0	96.0	99.0	109.0	97.0	120.0	27.0	NaN	NaN
2011-03-01	452.0	78.0	115.0	94.0	103.0	78.0	123.0	108.0	130.0	41.0	NaN	NaN	NaN
2011-04-01	300.0	65.0	62.0	64.0	60.0	69.0	65.0	78.0	22.0	NaN	NaN	NaN	NaN
2011-05-01	284.0	59.0	49.0	50.0	61.0	67.0	75.0	28.0	NaN	NaN	NaN	NaN	NaN
2011-06-01	242.0	45.0	39.0	64.0	57.0	83.0	25.0	NaN	NaN	NaN	NaN	NaN	NaN
2011-07-01	188.0	36.0	39.0	44.0	52.0	21.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-08-01	169.0	38.0	43.0	43.0	23.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-09-01	299.0	80.0	92.0	34.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-10-01	358.0	89.0	42.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-11-01	324.0	38.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-12-01	41.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Retention Rate Table:

Retention gives the percentage of active customers compared to the total number of customers.

CohortIndex Cohort_Month	1	2	3	4	5	6	7	8	9	10	11	12	13
2010-12-01	100.0	37.4	33.6	38.9	36.4	40.0	37.1	35.6	36.3	39.7	37.5	50.8	27.5
2011-01-01	100.0	23.0	26.9	23.7	32.1	29.5	24.9	24.9	30.2	33.1	36.5	12.5	NaN
2011-02-01	100.0	20.5	19.5	28.4	27.4	25.3	26.1	28.7	25.5	31.6	7.1	NaN	NaN
2011-03-01	100.0	17.3	25.4	20.8	22.8	17.3	27.2	23.9	28.8	9.1	NaN	NaN	NaN
2011-04-01	100.0	21.7	20.7	21.3	20.0	23.0	21.7	26.0	7.3	NaN	NaN	NaN	NaN
2011-05-01	100.0	20.8	17.3	17.6	21.5	23.6	26.4	9.9	NaN	NaN	NaN	NaN	NaN
2011-06-01	100.0	18.6	16.1	26.4	23.6	34.3	10.3	NaN	NaN	NaN	NaN	NaN	NaN
2011-07-01	100.0	19.1	20.7	23.4	27.7	11.2	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-08-01	100.0	22.5	25.4	25.4	13.6	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-09-01	100.0	26.8	30.8	11.4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-10-01	100.0	24.9	11.7	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-11-01	100.0	11.7	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-12-01	100.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

Heat Map :



2. Clustering by means of RFM Scores:

Customers are grouped and analysed based on their RFM scores. RFM scores are calculated for each customer based on their past purchases.

Recency score(R) :

R score is determined based on the customer's latest purchase. The more recent the last purchase ,the greater the R score.

```
r_labels = range(5, 0, -1)
r_groups = pd.qcut(dfrfm['rvalue'], q=5, labels=r_labels)
dfrfm = dfrfm.assign(R = r_groups.values)
dfrfm
```

	custid	rvalue	R
0	17850.0	3537.997352	1
1	13047.0	3267.100130	4
2	12583.0	3238.268880	5
3	13748.0	3331.200825	2
4	15100.0	3569.166102	1
...	...	...	...
4334	13436.0	3237.167569	5
4335	15520.0	3237.150208	5
4336	13298.0	3237.057847	5
4337	14569.0	3236.983541	5
4338	12713.0	3236.096041	5

4339 rows × 3 columns

Frequency score(F) :

F score indicates the number of purchases the customer has made over a given period of time.

```
f_labels = range(1, 6)
f_groups = pd.qcut(dfrfm['freq'], q=5, labels=f_labels)
dfrfm = dfrfm.assign(F = f_groups.values)
dfrfm
```

	custid	rvalue	R	freq	F
0	17850.0	3537.997352	1	300	5
1	13047.0	3267.100130	4	175	5
2	12583.0	3238.268880	5	248	5
3	13748.0	3331.200825	2	28	2
4	15100.0	3569.166102	1	3	1
...	...	...	...	...	...
4334	13436.0	3237.167569	5	12	1
4335	15520.0	3237.150208	5	18	2
4336	13298.0	3237.057847	5	2	1
4337	14569.0	3236.983541	5	12	1
4338	12713.0	3236.096041	5	38	3

4339 rows × 5 columns

Monetary Score(M) :

M score is determined by the total money spent by the customer. More the money spent, greater is the M score.

```
m_labels = range(1, 6)
m_groups = pd.qcut(dfrfm['mvalue'], q=5, labels=m_labels)
dfrfm = dfrfm.assign(M = m_groups.values)
dfrfm
```

	custid	rvalue	R	freq	F	mvalue	M
0	17850.0	3537.997352	1	300	5	5344.35	5
1	13047.0	3267.100130	4	175	5	3196.09	5
2	12583.0	3238.268880	5	248	5	7220.54	5
3	13748.0	3331.200825	2	28	2	948.25	4
4	15100.0	3569.166102	1	3	1	876.00	3
...	...	...	...	...	...	...	...
4334	13436.0	3237.167569	5	12	1	196.89	1
4335	15520.0	3237.150208	5	18	2	343.50	2
4336	13298.0	3237.057847	5	2	1	360.00	2
4337	14569.0	3236.983541	5	12	1	227.39	1
4338	12713.0	3236.096041	5	38	3	848.55	3

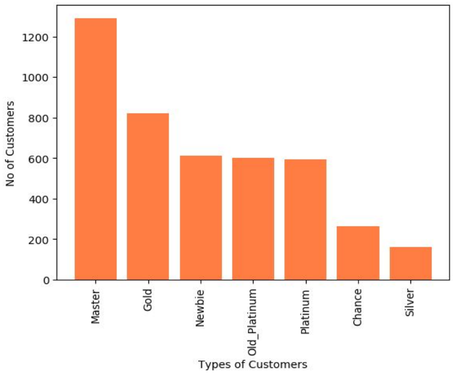
4339 rows × 7 columns

Now that the RFM scores are determined, the next step is to group the customers according to our requirements .

RFM values set according to our preferences:

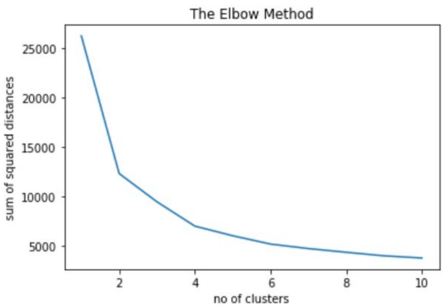
1. Newbies: customers with high R scores but low F and M scores.
2. Silver: customers with high R and M scores and less F score.
3. Gold: customers with high R and F but low M score.

4. Platinum: customers with high R,F,M scores.
5. Old_platinum : customers with low R scores but high F and M scores.
6. Chance: customers with low R and F scores but high M scores.



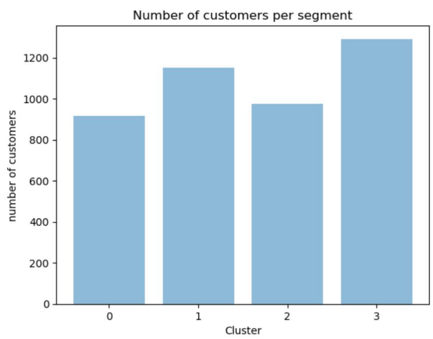
K-means Clustering:

The Elbow method helps us in determining the optimistic number of clusters.

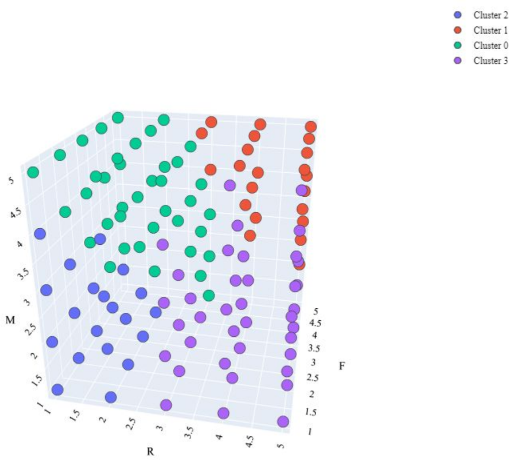


According to the graph k=4.

Number of customers per each cluster are as shown



Plotting the clusters:



Calculating average R,F,M scores for each cluster.

Cluster 1 has an elite of customers with high R,F,M scores, whereas cluster 0 has customers with low R,F,M values. Customers in cluster 2 are frequent and make high valued purchases but they have not made any purchase recently. And customers in cluster 3 have high R score but they are neither frequent nor do they spend more money on their orders.

VI. Conclusion

Customer Segmentation is the first task to make an effective showcasing technique and furthermore the foundation of customer relationship management. The cluster analysis of the chosen dataset explained a lot about the possible clusters in the target population of customers. We started with the analysis of the customer behaviour using cohort analysis, to know the customer commitment and then made clusters with RFM scores. RFM scores are calculated for each customer based on the past purchases. Once the number of clusters were determined using the elbow method, k-means clustering was used to make the clusters of the customers. Cluster 2 - old_platinum customers are frequent and make high valued purchases but they have not made any purchase recently, Cluster 0 - chance customers (low RFM scores), Cluster 3 - Newbies have high R score but they are neither frequent nor do they spend more money on their orders and Cluster 1 - platinum customers (high RFM scores). This practice of segmenting the customers will help in delivering a better customer experience by focusing on their needs and wants and improving the marketing investments by targeting the only those prone to the best clients

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