Behavioral Segmentation for Supermarket Customers Using Unsupervised Machine Learning Algorithms

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Abstract

Clustering is a machine learning technique to analyze data and to discover groups that share some similarities or closeness. It is useful for marketing segmentations because it allows classifying customers into groups based on certain characteristics. In literature, the most commonly studies segmentation types are: geographic, demographic, psychographic, behavioristic, volume, product-space, and benefit segmentation. This research is focused on behavioristic segmentations for supermarket chains.
Behavior patterns are the core of the behavioristic segmentation. It considers customers' attitude toward brands, the knowledge of brands, purchasing habits and frequency. The segmentation related to loyalty is crucial to identify loyal customers and to focus marketing strategies and tactics. The revenue depends greatly on that segment.
The research has been carried in four stages: analysis, design, development, and discussion. During the analysis, 1.073 customer loyalty surveys are preprocessed and analyzed. Two algorithms are employed during the investigation: Simple K-Means Algorithm (SKMA) and Expectation-Maximization Clustering (EMC).
While SKMA cluster sizes are 27%, 15%, 15%, 26%, and 17%, EMC cluster sizes are 2%, 29%, 24%, 32%, and 13%. In conclusion, both SKMA and EMC help segmenting supermarket customers based on their behavior. However, behavioral segmentation requires a deeper analysis since the cluster boundaries are not evident.

Keywords
Behavioristic Market Segmentation, Customer Loyalty, Machine Learning, Clustering Analysis, Supermarket Chains

1. Introduction
Market segmentation is one of the most relevant part of the marketing strategy. It was first introduced by W. Smith in 1056 and it has been deeply analyzed ever since. The objective of segmentation is to find a set of variable which allow identify homogeneous groups within a heterogeneous market to help focus the marketing strategies and tactics. To accomplish it, a variety of models and techniques have been developed and used thru the years, from simple statistical models to algorithms based on Artificial Intelligence (AI) (Mckechnie, 2006). Nowadays, the availability of new technologies makes possible to access customer data to be analyzed quickly. In the retail industry, for example, point of sales (POS) already allow apply data mining techniques and AI models.
Customer segmentation can be carried out following different criteria. For instance, it can be based on demographics (age, sex, income, occupation, social class, stage of life, Internet access and use), geographical (country, region, city, rural, density), behavioral (frequency of purchase, loyalty, where you buy, quantity purchased), purchase occasion (routine, special, hours or days of purchase, fixed place or while traveling), psychographic (lifestyle, personality, needs, values, attitudes, motivations), benefits (comfort, quality, economy, ease, speed, etc.), beliefs and attitudes (towards brands, products, purchase channels) (Tynan and Drayton, 1987; Rayport, 2001; Wyner, 2002; Kotler et al., 2009; Villarreal, R., 2014).

As expected, different segmentation criteria give rise to different results or segments. The degree of difficulty to complete the segmentation varies too. In particular, psychographic variables are the most complex mainly because they are related to the internal structure of individuals and are subjective in nature. Despite that, studies show that it is an approach that can be appropriate to guide marketing strategies (Barry and Weinstein, 2009; Kaze and Skapars, 2011; Scheuffelen et al., 2019).
Selecting segmentation criteria is not simple and yet crucial. It depends on the purpose of the segmentation and on the data availability, among others. Data-based segmentation is a useful tool to understand customer, however most of the times data are not easy to be understood (Dolnicar and Leisch, 2014; Venter et al., 2015). Once the segmentation is completed, it is necessary to identify the segments of mayor interest and the way they will be approached, which depends on the specific customers' needs and the products the company offers. (Wyner, 2002; Wedel and Kamakura, 2002).
Knowing the behavior of consumers is crucial to create value and communicate it. Along the years, several models to explain customers' behavior have been created. They are based on a paradigm commonly referred in the literature as CAB (cognition, affect, behavior). Howar and Sheth (1969) proposed that the brand recognition influences the attitude and the purchase intention.
This investigation make use of an extensive survey based on behavioral CAB paradigm to analyze supermarket customers by means of the following constructs: purchasing objectives (Baltas, 1997, Putrevu and Lord, 2001); supermarket image (Semeijn et. Al, 2004; Collins et. Al, 2002, Grewal et al., 1998); brand loyalty (Garretson et. Al, 2002; Harcar and Kucukemiroglu, 2006, Ailawadi, 2001); shopping experience (Ailawadi, 2001); convenience of the commercial relationship (Flavián et al., 2001); brand satisfaction (Burton et al., 1998); private label perception (Collins-Dodd, and Lindley, 2003; Garretson, 2002; Burton et al., 1998, Dick et al., 1995).

1.1 Objective
To carry out a customer behavioristic segmentation for supermarket chains by means of applying unsupervised machine learning techniques and clustering algorithms.

2. Literature Review

2.1 Market segmentation
Market segmentation can be understood as the split separation of the market in groups of customers with different characteristics and behavior, who might require separate products (Kotler and Armstrong, 1999).

Several criteria can be applied to define segment. Some of the most studied segmentation types in the literature are:

- Behavioral : brand loyalty, buyer journey stage, price sensitivity, purchasing style, etc.
- Benefit : customer service, quality, etc.
- Demographic : age, education level, gender, income, family members, status, religion, etc.
- Geographic : country, city, district, etc.
- Psychographic : hobbies, interests, lifestyle, etc.

2.2 Behavioral segmentation
This investigation is focused on the behavioral segmentation for supermarket customers. This type of segmentation classifies customers based on pattern of their behavior. Four types of behavioral segmentation have been widely studied: purchase behavior, occasion-based purchases, benefits sought, and customer loyalty

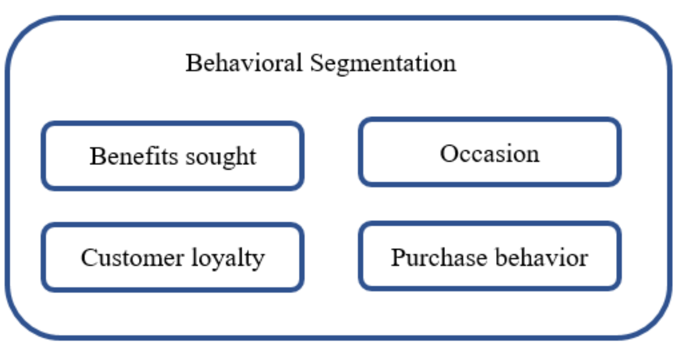

Figure 1. Behavioral segmentation

2.2.1 Segmentation based on purchase and usage behavior

This type of segmentation is useful to understand the stage of the buyer's journey in which customers are, and therefore to determine appropriate purchase triggers.

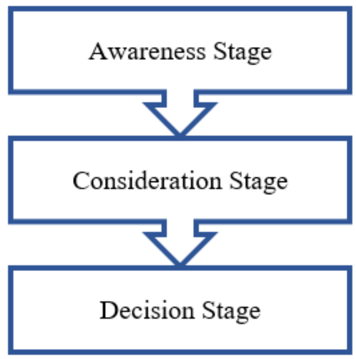

Figure 2. Consumer's journey-stage model

2.2.2 Segmentation based on occasion

This segmentation classifies customers based on the specific dates or moments of the day they purchase.

2.2.3 Segmentation based on sought benefits

This segmentation groups customers based on value proposition they look for. Understanding the benefits consumers expect can help redefined strategies and tactics to satisfice each segment.

2.2.4 Segmentation based on customer loyalty

This segmentation classifies customers based on the level of loyalty, which can be measured in terms of the purchase frequency.

2.3 Machine learning

Machine learning is usually referred as the branch of artificial intelligence (AI) that uses algorithms to find patterns and to learn from datasets through experience. There several types of machine learning algorithms: supervised, unsupervised, and reinforcement algorithms. In supervised learning, the training is carried out using labelled datasets. This means that the class or the value to be predicted is included in the dataset so it can be used for training. In the case of unsupervised learning, instead, the desired class is not known. The machine learning algorithms used in this work have been implemented with WEKA 3.8.5. (Witten et al., 2017)

2.4 Clustering algorithms

A clustering machine learning algorithm is an unsupervised machine learning algorithm used for discovering natural groupings or patterns. Some of the most popular clustering algorithms are:

- Agglomerative hierarchical clustering
- Density-based spatial clustering
- Expectation-maximization clustering (EMC)
- Simple K-Means algorithm (SKMA)
- Mean-shift clustering

2.5 Simple k-means algorithm (SKMA)

This type of clustering is probably the most popular of all. K-means clustering is an unsupervised machine learning algorithm that is used to group or categorize unlabeled data. The algorithm works iteratively and assign every new instance to one of the existing K clusters. The classification is carried out by similarity using the attributes or features of the instances.

2.5.1 Number of clusters

Finding the optimal number of clusters is important because not all values of K will produce the best model. There are several methods to determine the optimal number of clusters. Some of the most common are: average silhouette method, elbow method, and gap statistic method.

2.6 Expectation-maximization clustering (EMC)

The expectation-maximization (EM) algorithm is an iterative procedure for the maximum likelihood estimate of a parametric distribution. A particular case of this algorithm is the parameter estimation of a Gaussian Mixture Model (GMM) when the generating Gaussian of each observation is unknown, commonly known as Expectation-Maximization Clustering (EMC) (Garriga et al., 2016; Jung et al., 2014).

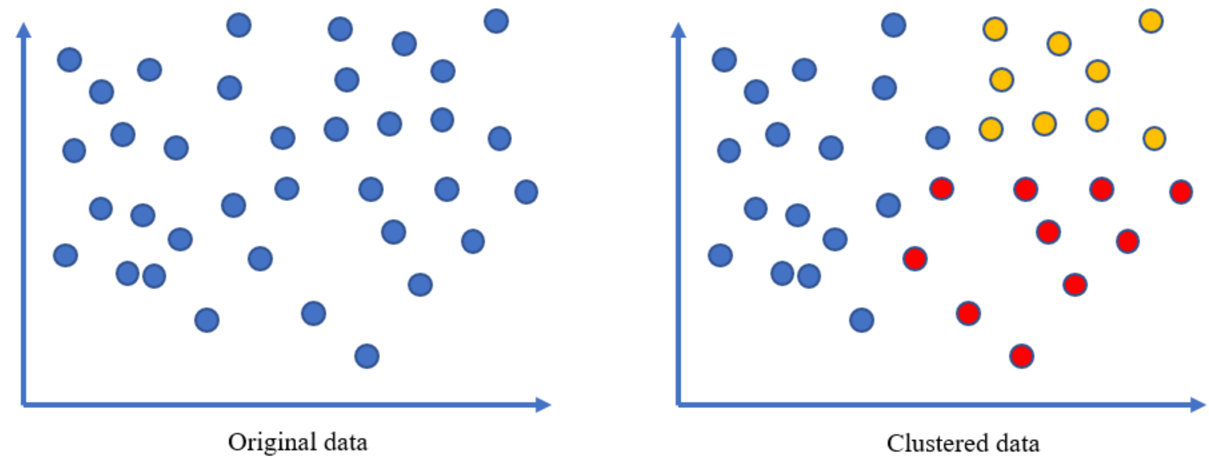

Figure 3. Clustering data

3. Methods

This investigation is carried out following a 4-stage model: analysis, design, construction, and discussion (Figure 5).

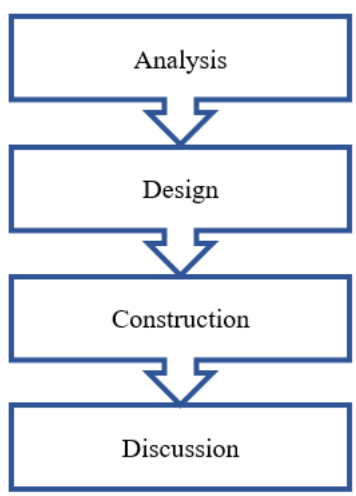

Figure 4. Four-stage model

3.1 Analysis

In the first stage, a complete review of the data gathered during an extensive survey about the purchasing habits and supermarket customers' preferences is carried out. The survey took place in Temuco, a city in the south of Chile with a population of approximately 221.000 inhabitants, and it considered five supermarket chains each of them

targeting different demographic market segments. These chains are quite distinguishable. For instance, one of them is focused on convenient stores, while other one offers exclusive products at higher prices.
The original questionnaire was based on previous well-documented survey created by renowned authors. It has 69 questions grouped in several domains such us: product quality, product availability and variety, value/price proposition, discount and loyalty campaigns, customer service, facility organization, etc. For the purposes of the present work only 25 questions grouped in 5 domains are considered, all of which were answered using a scale from 1 to 7 (Table 1).

Table 1. Selected domains

	Domain	Questions
D.1	Products' quality	4
D.2	Prices and discounts	6
D.3	Facility and service	5
D.4	Products' availability and variety	5
D.5	Overall purchase experience	5

Since the chains considered in the original survey target different demographic segments, this research focusses in only one of them. The selected chain is the middle of the price range, it counts with stores in different districts of the city and it has a well-established private label with a variety of products.

3.2 Design
The original unlabeled dataset, a matrix of 1073 rows (instances) by 25 columns, is prepared to be clustered by means of applying the algorithms SKMA and EMC. During the experiments, different number of clusters will be tested and compared. Survey domains and their corresponding questions are presented below (Table 2 and Table 3).

Table 2. Questions per domain

Domain	Q.3	Q.4	Q.5	Q.6	Q.7	Q.16	Q.17	Q.18	Q.19	Q.20	Q.21	Q.22	Q.23
D.1	✓	✓			✓								
D.2			✓	✓		✓							
D.3							✓	✓	✓	✓		✓	
D.4											✓		✓
D.5													

Table 3. Questions per domain (continuation)

Domain	Q.41	Q.42	Q.43	Q.44	Q.45	Q.46	Q.47	Q.48	Q.49	Q.50	Q.52	Q.53
D.1												✓
D.2								✓		✓	✓	
D.3												
D.4			✓				✓		✓			
D.5	✓	✓		✓	✓	✓						

3.3 Construction
As aforementioned, the objective of this investigation is to carry out the behavioral segmentation of a specific supermarket chain customers by means of applying clustering algorithms. However, behavioral segmentation differs significantly from other types. For instance, in demographic segmentation is evident whether customers are in certain age range. In this case, instead, a deeper analysis is required.
In particular, the survey data used in this work is organized in discrete values in the range 0 to 7. The summary of the answers to que questions are presented below (Table 4)

Table 3. Questions' answer summary

Question ID	Value 0	Value 1	Value 2	Value 3	Value 4	Value 5	Value 6	Value 7
Q.3	17	9	5	19	47	94	190	692

Q.4	17	30	18	53	110	265	247	333
Q.5	18	13	16	31	73	161	240	521
Q.6	21	87	40	71	105	190	219	340
Q.7	27	7	10	26	46	146	263	548
Q.16	19	8	9	48	87	144	347	411
Q.17	20	3	9	36	54	128	320	503
Q.18	23	2	8	35	64	140	307	494
Q.19	24	6	8	38	94	189	306	408
Q.20	24	3	7	31	85	137	333	453
Q.21	25	3	11	17	50	133	326	508
Q.22	23	6	3	35	100	161	333	412
Q.23	40	141	36	64	172	145	193	282
Q.41	25	92	54	91	144	278	230	159
Q.42	22	186	76	111	224	168	168	118
Q.43	51	134	52	108	264	170	152	142
Q.44	30	127	61	107	195	205	211	137
Q.45	30	29	11	60	104	177	337	325
Q.46	31	91	36	68	137	218	289	205
Q.47	34	116	41	100	133	226	228	195
Q.48	22	13	8	24	60	150	309	487
Q.49	21	6	9	9	73	154	309	492
Q.50	23	5	6	31	83	181	326	418
Q.52	24	15	16	29	96	188	340	365
Q.53	21	8	6	22	79	120	344	473

3.4 Discussion

Even though there exist more algorithms, the scope of this work is restricted to 2 of the most common algorithms: SKMA and EMC, which belong to a broader family usually called Gaussian mixture models.
The first algorithm studies, SMKA, requires the definition of K centroids and the iterations until certain degree of convergence to a local minimum is achieved. The latter, EMC, is meant to solve some of the weaknesses of SKMA. Rather than focusing on the accuracy of the classification, due to the nature of the behavioral clustering the interest is set on the number of clusters and the distribution of them.

4. Data Collection

Finding the optimal number of clusters for a given dataset requires the application of optimization algorithms. However, it might have some drawbacks. Especially when the number of clusters is too high to be applied in reality. The following tables present the data (instances) classification distribution when clustering algorithms are force to generate 1, 2, 3, 4, and 5 clusters (Table 4 and Table 5).

Table 4. SKMA with k=2, 3, 4, and 5

K	Cluster 1		Cluster 2		Cluster 3		Cluster 4		Cluster 5	
	%	Instances	%	Instances	%	Instances	%	Instances	%	Instances
2	55	585	45	488						
3	42	454	44	468	14	151				
4	26	282	19	204	16	175	38	412		
5	27	291	15	157	15	161	26	277	17	187

Table 5. EMC with 2, 3, 4, and 5 clusters

K	Cluster 1		Cluster 2		Cluster 3		Cluster 4		Cluster 5	
	%	Instances	%	Instances	%	Instances	%	Instances	%	Instances
2	38	404	62	669						
3	31	328	44	474	25	271				
4	41	444	25	266	2	26	31	337		
5	2	24	29	316	24	256	32	338	13	139

5. Results and Discussion

It might be interesting to determine the number of cluster that mathematically minimized the total squared distance between each data point and its closest centroid. SKMA can do that after several iterations. In spite of being the correct this approach might lead a not practical clustering. The following table presents how the dataset is distributed after applying SKMA with the optimal K equals to 16. The clustering produced by EMC is also shown. Implementing a marketing strategy for 16 different segment might be troublesome. From them, in the case of SKMA only 4 clusters concentrate between 10% and 20% of the data and only 2 of them in the case of EMC (Table 6).

Table 6. EMC and SKMA with 16 clusters

# Cluster	**EMC**		**SKMA**	
	%	Instances	%	Instances
1	4	47	10	104
2	9	92	8	88
3	2	22	5	57
4	7	70	7	80
5	4	45	13	135
6	5	53	9	99
7	8	89	5	56
8	17	181	4	44
9	10	102	7	72
10	12	130	5	59
11	1	15	6	66
12	13	141	7	76
13	2	22	5	51
14	3	30	3	31
15	1	10	3	34
16	2	24	2	21

5.1 Numerical Results

Behavioral segmentation might not be as evident as other types of segmentation due to the difficulty to differentiate customers. The definition of each cluster or segment requires a deep analysis. The success of a marketing strategy depends greatly on an appropriate understanding of customers purchase practices.

As mentioned earlier, the data used in this work were taken from an extensive supermarket customer survey whose questions are organized in several domains (Table 1 and Table2). The following tables present the distribution of the clusters generated by SKMA and EMC when the survey domains are separately analyzed (Table 7, Table 8, Table 9, Table 10, and Table 11).

Table 7. Clustering for domain D.1 (Q.3, Q.4, Q.7, and Q.53)

	SKMA		**EMC**	
Cluster	**%**	**Instances**	**%**	**Instances**
C.1	31	328	51	549
C.2	11	121	1	8
C.3	40	430	6	60
C.4	9	99	2	18
C.5	9	95	41	438

Table 8. Clustering for domain D.2 (Q.5, Q.6, Q.16, Q.48, Q.50, and Q.52)

	SKMA		**EMC**	
Cluster	**%**	**Instances**	**%**	**Instances**
C.1	35	374	2	22
C.2	17	179	34	360
C.3	9	101	35	376
C.4	15	156	18	196

C.5	25	263	11	119

Table 9. Clustering for domain D.3 (Q.17, Q.18, Q.19, Q.20, and Q.22)

	SKMA		EMC	
Cluster	**%**	**Instances**	**%**	**Instances**
C.1	26	282	2	26
C.2	19	202	32	345
C.3	18	188	9	101
C.4	8	82	36	382
C.5	30	319	20	219

Table 10. Clustering for domain D.4 (Q.21, Q.23, Q.43, Q.47, and Q.49)

	SKMA		EMC	
Cluster	**%**	**Instances**	**%**	**Instances**
C.1	30	325	31	334
C.2	21	227	30	322
C.3	20	214	4	41
C.4	17	186	22	235
C.5	11	121	13	141

Table 11. Clustering for domain D.5 (Q.41, Q.42, Q.44, Q.45 and Q.46)

	SKMA		EMC	
Cluster	**%**	**Instances**	**%**	**Instances**
C.1	34	365	3	28
C.2	25	266	15	159
C.3	14	150	33	355
C.4	13	141	12	129
C.5	14	151	37	402

6. Conclusion

Behavioral segmentation, different from other types, is not so evident and usually requires a deeper analysis to establish the difference between segments. This investigation takes advantage of an extensive supermarket customer survey to outline a segmentation based on the well-known SKMA and EMC clustering algorithms.

Clustering algorithms are a special case type of machine learning algorithms used to classified unlabeled data by means of grouping data points having similarities or some degree of closeness with each other.

Both SKMA and EMC are iterative optimization methods. Depending on the circumstances and necessities it might be possible to find the optimal number of clusters or define a given number that is more practical. Experiments revealed that the optimal number of clusters for the dataset is 16. However, only between 2 and 4 clusters concentrates more than 10% of the data points. A collection of small clusters or market segments might complicate excessively the design of an effective marketing campaign. Instead of that, a fixed number of clusters, from K=2 to K=5, was analyzed. In the case of five clusters, while SKMA cluster sizes are 27%, 15%, 15%, 26%, and 17%, EMC cluster sizes are 2%, 29%, 24%, 32%, and 13%.

An additional analysis was carried out to determine whether the nature of the survey's domain has an influence on the cluster definition. The difference in the sizes of the resulting clusters confirms that the segmentation depends, up to certain point, on the criteria being applied.

In conclusion, both clustering algorithms SKMA and EMC can help segmenting supermarket customers based on their behavior. However, behavioral segmentation requires a deeper analysis since the cluster borders usually are not evident.

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