MARKET SEGMENTATION ANALYSIS

This is the summarized version of the original book on Market Segment Analysis.
With the help of coordinated effort of all team members we have summarized the book. So, One can easily grab all the necessary information with less time.

APPROACH :-

Our team has read Entire book and grabbed a proper understanding of every process for effective Analysis.
Then the team leader assigned sub parts of the steps to all the team members including himself to extract a precise and understandable summary of the given task.
After Summarization every team member performs the illustration of Mcdonald's Case Study Individually in Python.

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Step 1: Deciding (not) to Segment

1) Implications of Committing to Market Segmentation

This step emphasises that the decision of whether or not to segment a market is an important one and should not be taken lightly. It argues that market segmentation can be a powerful tool for companies to target specific customer groups and tailor their marketing efforts accordingly. However, segmentation can also be time-consuming and costly and may not always yield meaningful results.

Market segmentation is an effective marketing strategy applied by organisations, but it is not always the best option. An organisation must commit to the segmentation strategy for the long term and invest resources in it. Before committing to segmentation, the organisation should understand the implications of the strategy, which include the need for long-term commitment, the willingness to make substantial changes and the potential development of new products, changes in pricing and distribution channels. These changes could influence the internal structure of the organisation, and it may need to be adjusted to target different market segments. Because of the major implications of such a long-term organisational commitment.

The decision to investigate the potential of a market segmentation strategy should be made at the managerial level and it should be systematically communicated across all organisational levels and units.

2) Implementation Barriers

The implementation of market segmentation can face various barriers. The first group of barriers is senior management, which includes a lack of leadership, commitment, involvement and resources. The second group of barriers is organisational culture, including resistance to change, bad communication, a lack of creative thinking, a lack of sharing of information and insights across organisational units, short-term thinking, an unwillingness to make changes and office politics. Lack of training and qualified marketing experts, data managers, and analysts can also represent major stumbling blocks.

Objective restrictions faced by the organisation, including a lack of financial resources and an inability to make the structural changes required, can also represent obstacles. Process-related barriers include not having clarified the objectives of the market segmentation exercise, lack of planning or bad planning, lack of structured processes to guide the team through all steps of the market segmentation process, lack of allocation of responsibilities and time pressure. Successful market segmentation requires a formal marketing function or at least a qualified marketing expert in the organisation. It is recommended that organisations organise around market segments rather than products to maximise the benefits of market segmentation.

Most of these barriers can be identified from the outset of a market segmentation study, and then proactively removed. If barriers cannot be removed, the option of abandoning the attempt of exploring market segmentation as a potential future strategy should be seriously considered.

3) Step 1 Checklist

This step also offers a checklist of questions an organisation may want to ask at this stage of the process. This first checklist includes not only tasks, but also a series of questions which, if not answered in the affirmative, serve as knockout criteria.

Step 2: Specifying the Ideal Target Segment

1) Segment Evaluation Criteria

Market segmentation analysis is driven primarily by the desire of an organisation to better cater to a part of the market and in so doing, secure a competitive advantage. At the end of the segmentation analysis, the organisation needs to select one or more target segments. To make this selection process as easy as possible, it is useful to think about what an ideal target segment might look like from the perspective of the organisation at the early stages of the market segmentation analysis. This step discusses how such a conversation can be facilitated. The outcome of this process directly informs the subsequent, more technical steps of the process.

The second step of market segmentation analysis involves defining the ideal target segment for a product or service. The success of this step relies heavily on user input and their involvement throughout the process. The organisation must define two sets of segment evaluation criteria, knock-out criteria and attractiveness criteria.

2) Knock-Out Criteria

Knock-out criteria are used to determine if market segments resulting from the market segmentation analysis qualify to be assessed using segment attractiveness criteria. The knock-out criteria are essential features of segments that the organisation would consider targeting. Knock-out criteria automatically eliminate some of the available market segments.

The first set of such criteria was suggested by Kotler and includes substantiality, measurability and accessibility.

Additional criteria that fall into the knock-out criterion category :

- The segment must be **homogeneous**
- The segment must be **distinct**
- The segment must be **large enough**
- The segment must be **matching**
- The segment must be **matching**
- The segment must be **reachable**

Knock-out criteria must be understood by senior management, the segmentation team, and the advisory committee. Most of them do not require further specification, but some do.

3)Attractiveness Criteria

Attractiveness criteria are used to evaluate the relative attractiveness of the remaining market segments. It determine the overall attractiveness of each market segment. Attractiveness criteria are diverse and represent a shopping list for the segmentation team, and they need to select which criteria they want to use to determine how attractive potential target segments are. The attractiveness across all criteria determines whether a market segment is selected as a target segment in Step 8 of market segmentation analysis.

4) Implementing a Structured Process

Following a structured process is necessary when assessing market segments and the use of a segment evaluation plot showing segment attractiveness along one axis and organisational competitiveness on the other is the most popular approach. The segment attractiveness and organisational competitiveness values are determined by the segmentation team, and factors that constitute both need to be negotiated and agreed upon. It is widely accepted in the field of market segmentation that using a structured process is beneficial. The most popular approach is to use a segment evaluation plot to assess segment attractiveness and organizational competitiveness. The criteria for these factors need to be negotiated and agreed upon by the segmentation team, and a large number of possible criteria should be investigated before agreement is reached. It is recommended that no more than six factors are used as the basis for calculating the criteria. This process should ideally be completed by a team of people, with representatives from all organizational units, as this affects every unit. The segment evaluation plot cannot be completed in Step 2 of the market segmentation analysis, but selecting the attractiveness criteria for market segments at this stage ensures that all relevant information is captured when collecting data. At the end of this step, the market segmentation team should have a list of approximately six segment
attractiveness criteria with weights indicating their importance to the organization. These allocations should be negotiated until agreement is reached, and approval by the advisory committee should be sought.

Step 3: Collecting Data

- The third step in market segmentation analysis is collecting data. This involves gathering information about the target market and potential customer segments, including demographic, psychographic, behavioral, and other relevant data.

- The data collection process can involve a variety of methods, including surveys, focus groups, interviews, observations, and secondary data sources such as market research reports, government data, and industry publications.

- To ensure that the data collected is relevant and useful for segmentation analysis, it's important to have a clear understanding of the research objectives and to design the data collection methods accordingly. This may involve creating survey questions that are specific to the target market or using observational methods to understand how customers interact with products or services

- Once the data has been collected, it will need to be analyzed and processed to extract insights and identify potential customer segments. This analysis will involve exploring the data and looking for patterns and trends that can be used to segment the market effectively. By collecting and analyzing relevant data, companies can gain valuable insights into customer needs, preferences, and behavior, which can be used to develop targeted marketing strategies and improve the effectiveness of their marketing efforts.

- For McDonald's, collecting data might involve conducting surveys and focus groups to gather information about customer preferences and behavior, as well as using secondary data sources such as market research reports and government data to supplement the information collected. The data collected could be used to identify potential customer segments based on factors such as age, gender, taste preferences, and visit frequency.

STEP-4:

Implications of committing to Market Segmentation

Market segmentation can be a key marketing strategy, but it requires a long-term commitment and substantial investments in research, product development, pricing, distribution channels, and communication. To maximize the benefits of market segmentation, organizations need to organize around market segments, rather than products. The decision to pursue a market segmentation strategy should be made at the highest execution level and systematically communicated and reinforced across all organizational levels and units.

Implementation Barriers

Several barriers to the successful implementation of a market segmentation strategy in organizations are identified in various books, including lack of leadership and resources from senior management, resistance to change and lack of market orientation in the organizational culture, lack of training and expertise, objective restrictions, process-related barriers, and difficulty in understanding and interrupting results. These barriers can be proactively removed, but if not, abandoning the attempt should be considered. To succeed, dedication, patience, and a willingness to appreciate the challenges are required.

Specifying the Ideal Target Segment

Segment Evaluation Criteria

The third layer of market segmentation analysis relies heavily on user input throughout the process rather than just at the beginning or end. The organization must determine two sets of criteria for segment evaluation: knock-out criteria (essential, non-negotiable features) and attractiveness criteria (used to evaluate the relative attractiveness of remaining segments). The literature proposes a wide array of possible criteria, but the segmentation team must select which ones to use and assess their relative importance. Knockout criteria automatically eliminate some segments, while attractiveness criteria are negotiated and then applied to determine the overall relative attractiveness of each market segment.

Knock-Out Criteria

Knock-out criteria are used to determine if market segments qualify for assessment using segment attractiveness criteria. The criteria include homogeneity, distinctiveness, size, matching strengths of the organization, identifiability, and reachability. These criteria are nonnegotiable and must be understood by senior management, the segmentation team, and the advisory committee. The exact minimum viable target segment size needs to be specified.

Implementing a Structured Process

The article discusses the importance of a structured approach to evaluating market segments and recommends the use of a segment evaluation plot to assess segment attractiveness and organizational competitiveness. It suggests that a team of people should determine the criteria for both these factors, and representatives from various organizational units should be included in the process. The article emphasizes the importance of selecting attractiveness criteria at an early stage in the process to facilitate data collection and make target segment selection easier. It also recommends allocating weights to each criterion based on their relative importance, through negotiation and agreement among team members and approval from the advisory committee.

Collecting Data

Segmentation Variables

Table 5.1 Gender as a possible segmentation variable in commonsense market segmentation

Sociodemographics		Travel behaviour	Benefits sought				
gender	age	Nº of vacations	relaxation	action	culture	explore	meet people
Female	34	2	1	0	1	0	1
Female	55	3	1	0	1	0	1
Female	68	1	0	1	1	0	0
Female	34	1	0	0	1	0	0
Female	22	0	1	0	1	1	1
Female	31	3	1	0	1	1	1
Male	87	2	1	0	1	0	1
Male	55	4	0	1	0	1	1
Male	43	0	0	1	0	1	0
Male	23	0	0	1	1	0	1
Male	19	3	0	1	1	0	1
Male	64	4	0	0	0	0	0
segmentation variable	descriptor variables						

Table 5.2 Segmentation variables in data-driven market segmentation

Sociodemographics		Travel behaviour	Benefits sought				
gender	age	Nº of vacations	relaxation	action	culture	explore	meet people
Female	34	2	1	0	1	0	1
Female	55	3	1	0	1	0	1
Male	87	2	1	0	1	0	1
Female	68	1	0	1	1	0	0
Female	34	1	0	0	1	0	0
Female	22	0	1	0	1	1	1
Female	31	3	1	0	1	1	1
Male	55	4	0	1	0	1	1
Male	43	0	0	1	0	1	0
Male	23	0	0	1	1	0	1
Male	19	3	0	1	1	0	1
Male	64	4	0	0	0	0	0
descriptor variables			segmentation variables				

The article discusses the importance of empirical data in market segmentation, which forms the basis of both commonsense and data-driven approaches. In commonsense segmentation, a single characteristic is used as the segmentation variable to split the sample into market segments. In contrast, data-driven segmentation involves multiple segmentation variables to identify naturally existing or artificially created market segments. Good empirical data is critical for developing a valid segmentation solution, and it can come from a range of sources, such as survey studies, observations, and experimental studies. The source that delivers data most closely reflecting actual consumer behavior is preferable. The quality of empirical data determines the quality of the extracted market segments and the quality of the descriptions of the resulting segments, which is critical for developing a customised product, pricing strategy, distribution channel, and communication channel for advertising and promotion.

Segmentation Variables

Before data for market segmentation is collected, an organization must decide which segmentation criterion to use. The most common criteria are geographic, socio-demographic, psychographic, and behavioral. There are many different segmentation criteria available, but the recommendation is to use the simplest possible approach that works for the product or service at the least possible cost. The decision cannot be outsourced and requires prior knowledge about the market. The relevant differences between consumers for market segmentation are profitability, bargaining power, preferences, barriers to choice, and interaction effects.

Geographic Segmentation

Geographic segmentation is the original and simplest segmentation criterion used in market segmentation, where a consumer's location of residence serves as the only criterion to form market segments. It is useful when targeting consumers in specific regions or countries, but it may not account for other important characteristics relevant to marketers. Despite its potential shortcomings, geographic information has experienced a revival in international market segmentation studies aiming to extract market segments across geographic boundaries.

Socio-Demographic Segmentation

Socio-demographic segmentation criteria, such as age, gender, income, and education, can be useful in certain industries, but they may not always provide sufficient insight into consumer behavior and preferences. While demographic factors may explain some variance in consumer behavior, they are not always the primary cause of product preferences. Yankelovich and Meer (2006) argue that values, tastes, and preferences are more influential in consumers' buying decisions and, therefore, may be a more useful basis for market segmentation. Haley (1985) estimates that demographics only explain about 5% of the variance in consumer behavior.

Psychographic Segmentation

Psychographic segmentation is a grouping of people according to psychological criteria such as beliefs, interests, preferences, aspirations, or benefits sought when purchasing a product. It is a more complex approach than geographic or socio-demographic criteria because it is difficult to find a single characteristic that will provide insight into the psychographic dimension of interest. Benefit and lifestyle segmentation are popular psychographic segmentation approaches. The psychographic approach has the advantage of reflecting the underlying reasons for differences in consumer behavior. However, determining segment memberships for consumers can be complex, and the reliability and validity of the empirical measures used to capture psychographic dimensions are crucial.

Behavioural Segmentation

Behavioural segmentation is an approach to segment extraction that groups people based on their actual behaviour or reported behaviour, such as prior experience with the product, frequency of purchase, and information search behaviour. This approach is advantageous because it uses the very behaviour of interest as the basis for segmentation, without the need for the development of valid measures for psychological constructs. However, behavioural data may not always be readily available, especially when targeting potential customers who have not previously purchased the product.

Choice of Variables

In both commonsense and data-driven segmentation, it is crucial to carefully select the variables included as segmentation variables to ensure the quality of the segmentation solution. In data-driven segmentation, all relevant variables must be included while avoiding unnecessary variables that can cause respondent fatigue and make the extraction of optimal segments more difficult. Noisy variables or masking variables, which do not contribute to identifying the correct market segments, can negatively affect the segmentation solution. To avoid these issues, it is recommended to ask all necessary and unique questions while avoiding redundant questions. A good questionnaire requires conducting exploratory or qualitative research to ensure that no critical variables are omitted.

Response Options

The response options provided in surveys can affect the suitability of data for segmentation analysis. Binary and metric data are preferred, as they allow for clear distance measures. Nominal and ordinal data are less suitable for segmentation analysis, as the distance between answer options is not clearly defined. Visual analogue scales can be used to capture fine nuances of responses. Binary response options have been shown to outperform ordinal options, especially when formulated in a level-free way.

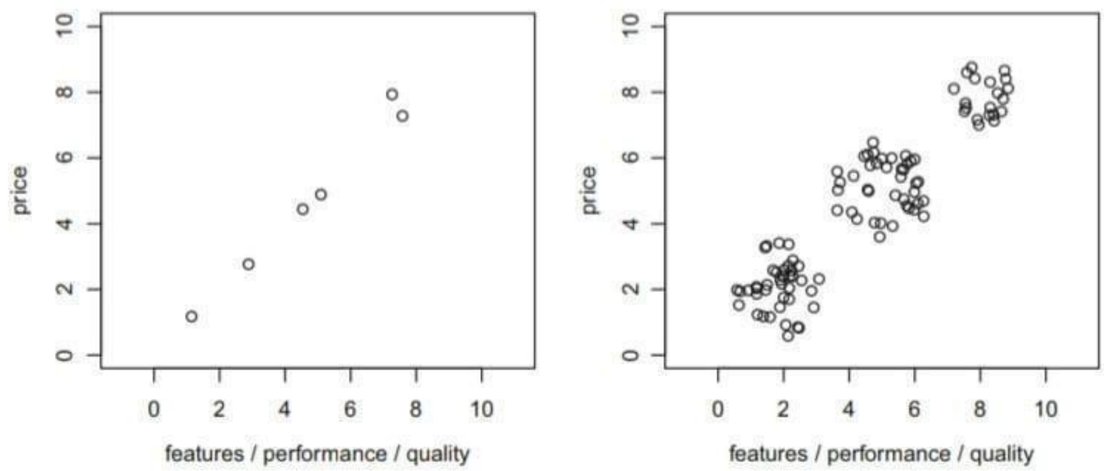
Response Styles

Survey data is vulnerable to response biases, which can result in response styles that affect segmentation analysis. Response biases can cause respondents to answer questions in a consistent way that is not related to the specific content of the questions. These biases can lead to misleading segmentation results, making it essential to minimize the risk of capturing response styles when collecting data for market segmentation. Identifying and removing respondents affected by response styles can help prevent this problem. Additional analyses may also be necessary to exclude the possibility of response style bias in attractive market segments.

Sample Size

The issue of sample size in market segmentation analysis is crucial. Insufficient sample size can make it impossible to determine the correct number of market segments, while sufficient sample size makes it easy to identify both the number and nature of segments.

Different studies have proposed different rules of thumb for sample size, ranging from at least 2p (or five times 2p) to 10 · p · k, where p is the number of segmentation variables and k is the number of segments.



Simulation studies have shown that sample size has a significant effect on the correctness of segment recovery, as measured by the adjusted Rand index, which assesses the congruence between two segmentation solutions. Overall, market segmentation analysis requires careful consideration of sample size to ensure the accuracy and validity of the results.

Extracting Segments:

1. Distance based methods:

1.1. Distance Measures:

Consider a fictitious data set on tourist activities:

	beach	action	culture
Anna	100	0	0
Bill	100	0	0
Frank	60	40	0
Julia	70	0	30
Maria	80	0	20
Michael	0	90	10
Tom	50	20	30

Each row represents an observation (in this case a tourist), and every column represents a variable (in this case a vacation activity). Mathematically, this can be represented as an n × p matrix where n stands for the number of observations (rows) and p for the number of variables (columns).

Some criteria for distance measures are as follows:

- **Symmetry:**

$$d(\mathbf{x}, \mathbf{y}) = d(\mathbf{y}, \mathbf{x})$$

- **The distance of a vector to itself and only to itself is 0:**

$$d(\mathbf{x}, \mathbf{y}) = 0 \Leftrightarrow \mathbf{x} = \mathbf{y}.$$

- **Triangle inequality:**

$$d(\mathbf{x}, \mathbf{z}) \leq d(\mathbf{x}, \mathbf{y}) + d(\mathbf{y}, \mathbf{z})$$

Some of the distance measures are as follows:

- **Euclidean Distance:**

$$d(\mathbf{x}, \mathbf{y}) = \sqrt{\sum_{j=1}^{p} (x_j - y_j)^2}$$

- **Manhattan Distance:**

$$d(\mathbf{x}, \mathbf{y}) = \sum_{j=1}^{p} |x_j - y_j|$$

Implementation of Euclidean distance:

```
import numpy as np

# Define the data matrix
X = np.array([[100, 0, 0],
              [0, 0, 40],
              [0, 0, 0],
              [70, 0, 0],
              [80, 30, 20],
              [0, 20, 10],
              [50, 20, 30]])

# Compute the Euclidean distance matrix
dist_matrix = np.zeros((7, 7))
for i in range(7):
    for j in range(7):
        dist_matrix[i, j] = np.linalg.norm(X[i] - X[j])

# Print the distance matrix
print(dist_matrix)
```

Output:

```
[[  0.         107.70329614 100.          30.          41.23105626
  102.46950766  61.64414003]
 [107.70329614   0.          40.          80.62257748  87.74964387
   36.05551275  54.77225575]
 [100.          40.           0.          70.          87.74964387
   22.36067977  61.64414003]
 [ 30.          80.62257748  70.           0.          37.41657387
   73.48469228  41.23105626]
 [ 41.23105626  87.74964387  87.74964387  37.41657387   0.
   81.24038405  33.1662479 ]
 [102.46950766  36.05551275  22.36067977  73.48469228  81.24038405
    0.          53.85164807]
 [ 61.64414003  54.77225575  61.64414003  41.23105626  33.1662479
   53.85164807   0.        ]]
```

Implementation of Manhattan Distance:

```python
import numpy as np
from scipy.spatial.distance import cityblock

# Define the data matrix
X = np.array([[100, 0, 0],
              [0, 0, 0],
              [0, 40, 0],
              [0, 0, 70],
              [0, 80, 30],
              [90, 20, 0],
              [50, 20, 30]])

# Calculate the distance matrix using Manhattan distance
dist_matrix = np.zeros((7, 7))
for i in range(7):
    for j in range(7):
        dist_matrix[i, j] = cityblock(X[i], X[j])

print(dist_matrix)
```

Output:

```
[[  0. 100. 140. 170. 210.  30. 100.]
 [100.   0.  40.  70. 110. 110. 100.]
 [140.  40.   0. 110.  70. 110. 100.]
 [170.  70. 110.   0. 120. 180. 110.]
 [210. 110.  70. 120.   0. 180. 110.]
 [ 30. 110. 110. 180. 180.   0.  70.]
 [100. 100. 100. 110. 110.  70.   0.]]
```

1.2. Hierarchical Methods:

a. Divisive hierarchical clustering methods start with the complete data set X and splits it into two market segments in a first step. Then, each of the segments is again split into two segments. This process continues until each consumer has their own market segment.

b. Agglomerative hierarchical clustering approaches the task from the other end. The starting point is each consumer representing their own market segment. Step-by-step, the two market segments closest to one another are merged until the complete data set forms one large market segment.

c. Underlying both divisive and agglomerative clustering is a measure of distance between groups of observations (segments). This measure is determined by specifying a distance measure d(x, y) between observations (consumers) x and y, and a linkage method. Some linkage methods are as follows:

- **Single Linkage:** The distance between the two closest observations of the two sets.

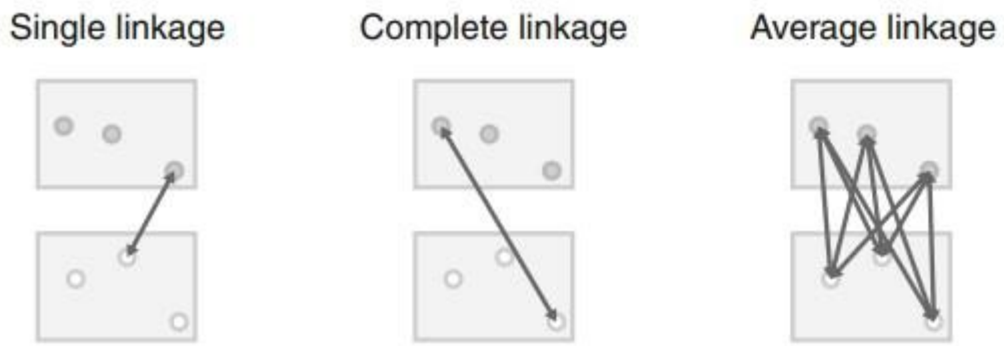
$$l(\mathcal{X}, \mathcal{Y}) = \min_{\mathbf{x}\in\mathcal{X}, \mathbf{y}\in\mathcal{Y}} d(\mathbf{x}, \mathbf{y})$$

- **Complete Linkage:** The distance between the two observations of the two sets that are farthest away from each other.

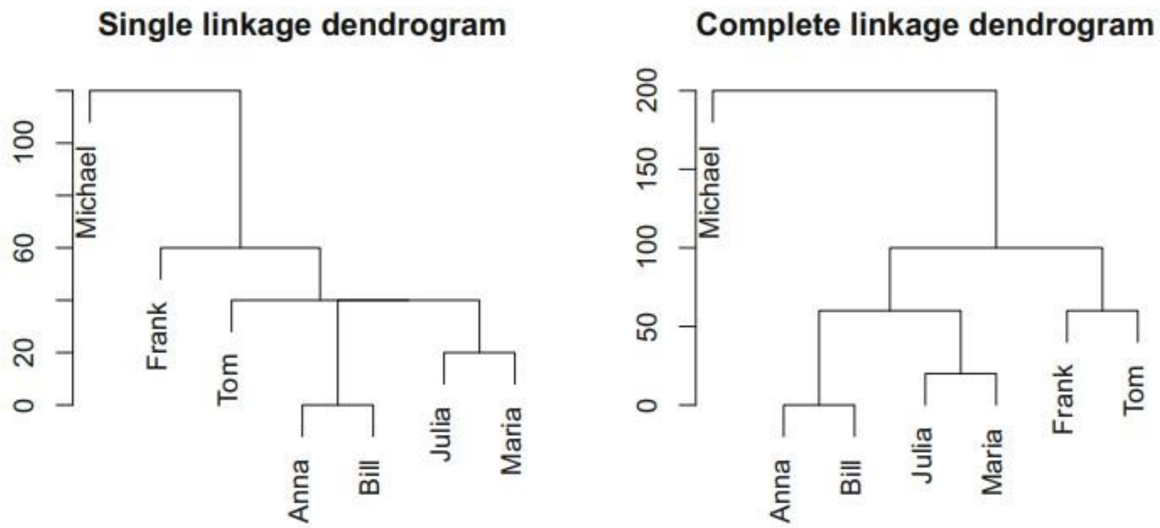
$$l(\mathcal{X}, \mathcal{Y}) = \max_{\mathbf{x} \in \mathcal{X}, \mathbf{y} \in \mathcal{Y}} d(\mathbf{x}, \mathbf{y})$$

- **Average Linkage:** The mean distance between observations of the two sets.

$$l(\mathcal{X}, \mathcal{Y}) = \frac{1}{|\mathcal{X}||\mathcal{Y}|} \sum_{\mathbf{x} \in \mathcal{X}} \sum_{\mathbf{y} \in \mathcal{Y}} d(\mathbf{x}, \mathbf{y}).$$



d. The result of hierarchical clustering is typically presented as a dendrogram. Eg: Dendogram for single linkage and complete linkage in the tourist dataset is

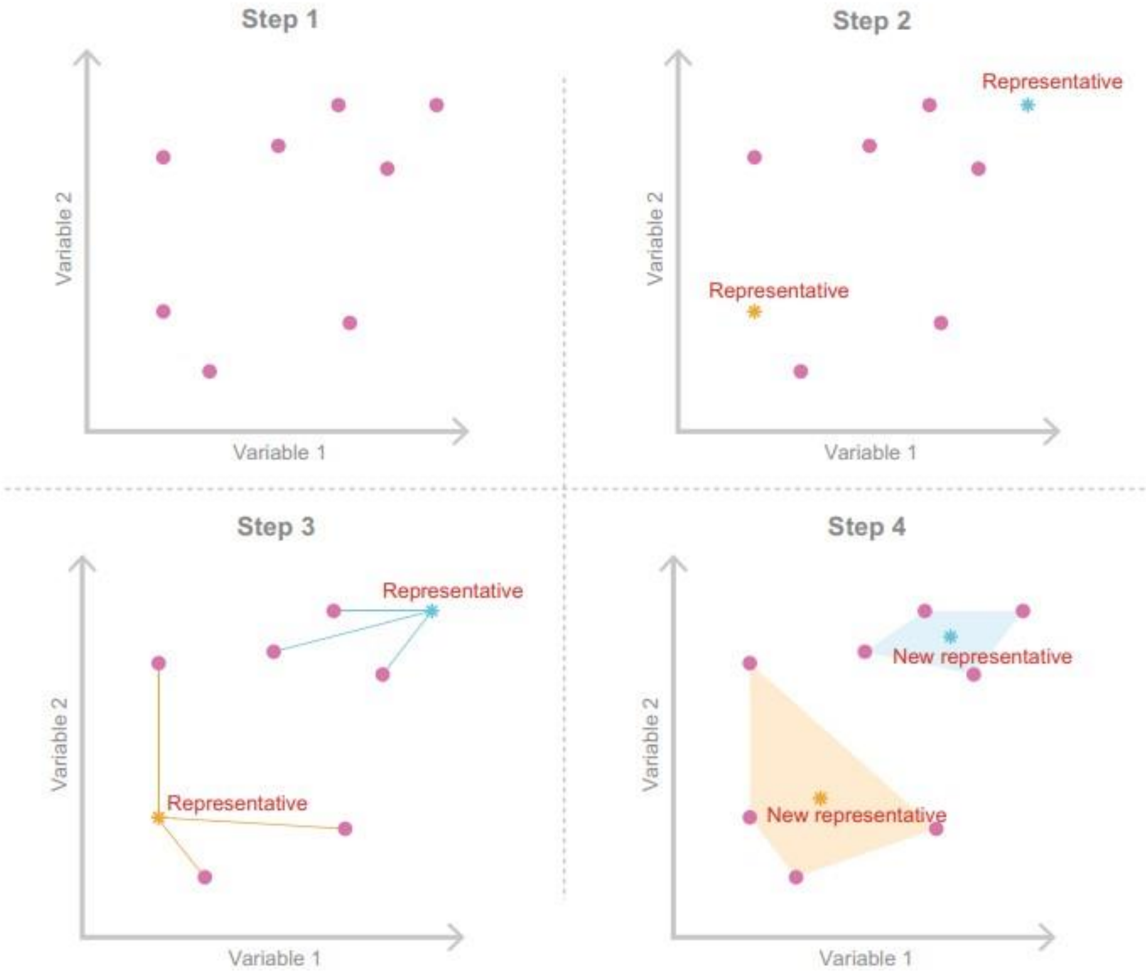


1.3 Partitioning Methods:

K means:

Steps for k means algorithm:

- Specify the desired number of segments k.
- Randomly select k observations (consumers) from data set and use them as initial set of cluster centroids.
- Assign each observation to the closest cluster centroid.
- Recompute the cluster centroids by holding cluster membership fixed, and minimising the distance from each consumer to the corresponding cluster centroid.
- Repeat from step 3 until convergence or a pre-specified maximum number of iterations is reached.



Improved K means:

- Using randomly drawn consumers is suboptimal because it may result in some of those randomly drawn consumers being located very close to one another, and thus not being representative of the data space.

- This leads to **local optimum**.
- The best approach is to randomly draw many starting points, and select the best set.

Hard Competitive Learning:

- Hard competitive learning randomly picks one consumer and moves this consumer's closest segment representative a small step into the direction of the randomly chosen consumer.

Neural Gas and Topology Representing Networks:

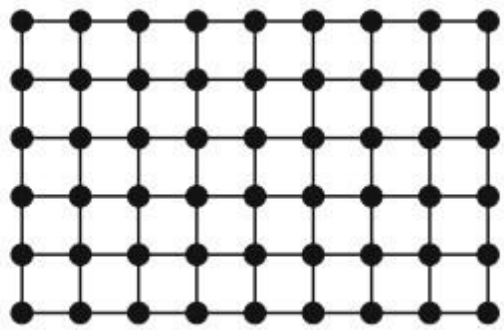
- In the Neural Gas the segment representative (centroid)is moved towards the randomly selected consumer.
- The Topology Representing Networks count how often each pair of segment representatives (centroids) is closest and second closest to a randomly drawn consumer.

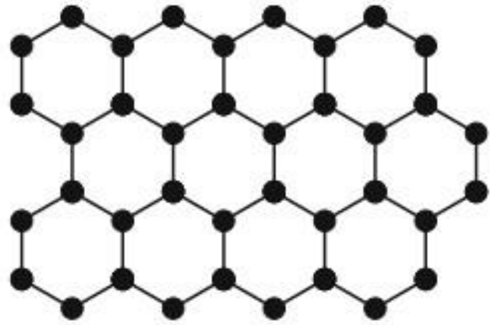
Self Organising Maps:

- A single random consumer is selected from the data set, and the closest representative for this random consumer moves a small step in their direction.
- The representatives which are direct grid neighbours of the closest representative move in the direction of the selected random consumer.

Neural Networks:

- The most popular method from this family of algorithms uses a so-called single hidden layer perceptron.
- The network has three layers. The input layer takes the data as input. The output layer gives the response of the network. In-between the input and output layer is the so-called hidden layer.





1.4 Hybrid Approaches:

Two step clustering:

- The two steps consist of run a partitioning procedure followed by a hierarchical procedure.

Bagged Clustering:

- Bagged clustering also combines hierarchical clustering algorithms and partitioning clustering algorithms, but adds bootstrapping.

2. Model based methods:

Properties of Model based methods:

- Each market segment has a certain size.

$$z \sim \text{Multinomial}(\pi).$$

- The members of each market segment have segment-specific characteristics.

$$f(y|x, \theta_z).$$

Note: These functions together with their parameters forms a finite mixture model.

$$\sum_{h=1}^{k} \pi_h f(y|x, \theta_h), \quad \pi_h > 0, \quad \sum_{h=1}^{k} \pi_h = 1.$$

Different statistical frameworks are available for estimating the parameters of the finite mixture model:

- **Maximum Likelihood Estimation(MLE):** It aims at determining the parameter values for which the observed data is most likely to occur.
- **Bayesian framework Estimation:** a Bayesian approach is pursued, mixture models are usually fitted using Markov chain Monte Carlo methods.

2.1 Finite Mixtures of Distributions:

The simplest case of model-based clustering has no independent variables x, and simply fits a distribution to y.

Normal Distributions: A mixture of normal distributions can be used for market segmentation when the segmentation variables are metric.

Binary Distributions: In this case, the p segmentation variables in the vector y are not metric, but binary (meaning that all p elements of y are either 0 or 1).

2.2 Finite Mixtures of Regression:

- Finite mixture of regression models assume the existence of a dependent target variable y that can be explained by a set of independent variables x.
- The functional relationship between the dependent and independent variables is considered different for different market segments.

Algorithms with Integrated Variable Selection

Traditional segmentation algorithms assume that all segmentation variables contribute to determining the segmentation solution, but this is not always the case as some variables may be redundant or noisy. Hence, Pre-processing methods, such as the filtering approach, can identify and exclude such variables. However, for binary data, it is challenging to pre-screen variables one by one. Therefore, suitable segmentation variables need to be identified during the segment extraction process.

Two algorithms for binary segmentation variables that select suitable segmentation variables while extracting segments are: biclustering and the variable selection procedure for clustering binary data (VSBD). Additionally, factor-cluster analysis, a two-step approach can be used to compress segmentation variables into factors before segment extraction.

Biclustering Algorithms

Biclustering algorithms are a family of algorithms that cluster both consumers and variables simultaneously. They exist for any kind of data, including metric and binary data. In this case, the focus is on binary data where these algorithms aim at extracting market segments containing consumers who all have a value of 1 for a group of variables, which together form the bicluster.

Several popular biclustering algorithms exist, and they differ in how a bicluster is defined. In the simplest case, a bicluster is defined for binary data as a set of observations with values of 1 for a subset of variables. The biclustering algorithm extracts these biclusters by following a sequence of steps. The starting point is a data matrix where each row represents one consumer, and each column represents a binary segmentation variable. The algorithm then rearranges the rows and columns of the data matrix to create a rectangle with identical entries of 1s at the top left of the data matrix. The algorithm assigns the observations falling into this rectangle to one bicluster, and the segmentation variables defining the rectangle are active variables for this bicluster. The algorithm removes from the data matrix the rows containing the consumers who have been assigned to the first bicluster and repeats the procedure from step 1 until no more biclusters of sufficient size can be located.

Biclustering is particularly useful in market segmentation applications with many segmentation variables as it avoids arriving at suboptimal groupings of consumers in such situations. Biclustering also has a number of other advantages, including no data transformation, automatic outlier detection, and the ability to handle missing values.

Variable Selection Procedure for Clustering Binary Data (VSBD)

The VSBD method is based on the k-means algorithm as a clustering method and assumes that not all variables available are relevant to obtain a good clustering solution. The method first identifies the best small subset of variables to extract segments, based on the within-cluster sum-of-squares criterion, which is the criterion minimized by the k-means algorithm. The procedure adds additional variables one by one, selecting the variable that leads to the smallest increase in the within-cluster sum-of-squares criterion. The procedure stops when the increase in within-cluster sum-of-squares reaches a threshold. Brusco recommends using the Ratkowsky and Lance index for the complete data to select the number of segments. The VSBD procedure selects only relevant variables and removes irrelevant ones, easing interpretation. The VSBD algorithm was applied to the Australian travel motives dataset using the default settings, and the procedure selected only six out of the twenty available variables. The final solution resulted in six groups, and the selected variables were "rest and relax," "realize creativity," "health and beauty," "cosiness/familiar atmosphere," "do sports," and "everything organized." The VSBD method helps to identify the correct segment structure and eases interpretation.

Variable Reduction: Factor-Cluster Analysis

Factor-cluster analysis is a two-step process used in market segmentation analysis to extract market segments from factor scores resulting from factor analysis. In the first step, segmentation variables are factor analyzed, and in the second step, the original segmentation variables are discarded, and the factor scores are used to extract market segments. This approach is conceptually legitimate if the empirical data results from a validated psychological test battery designed specifically to contain variables that load onto factors.

However, factor-cluster analysis is more commonly used when the number of segmentation variables is too high, and the sample size is not sufficient. According to simulation studies, the number of consumers in a data set should be at least 100 times the number of segmentation variables. Factor analysis leads to a loss of information, and running factor-cluster analysis to deal with the problem of having too many segmentation variables in view of their sample size lacks conceptual legitimization and comes at a substantial cost. Factors-cluster results are more difficult to interpret and have no concrete meaning, making the translation process from segments to practical recommendations for the marketing mix challenging.

In conclusion, factor-cluster analysis is legitimate when the empirical data results from a validated psychological test battery designed specifically to contain variables that load onto factors. However, it is generally not advisable to use factor-cluster analysis when the number of segmentation variables is too high in view of their sample size, as it leads to a loss of information, lacks conceptual legitimization, and results in difficulty interpreting the factor-cluster results. It is, therefore, better to extract segments from the space of the original consumer data, the original segmentation variables, to obtain better results.

Data Structure Analysis

The process of extracting market segments is inherently exploratory, regardless of the extraction algorithm used, making it difficult to validate solutions using traditional optimization criteria. Instead, validation in the context of market segmentation typically refers to assessing the reliability or stability of solutions across repeated calculations after slightly modifying the data or algorithm. This approach, referred to as stability-based data structure analysis, provides valuable insights into the properties of the data, including whether natural, distinct, and well-separated market segments exist in the data or not. If they do, they can be easily revealed, but if they do not, users and data analysts need to explore a large number of alternative solutions to identify the most useful segment(s) for the organization. Data structure analysis can also help to choose a suitable number of segments to extract, using cluster indices, gorge plots, global stability analysis, and segment level stability analysis.

Cluster Indices

The process of market segmentation analysis is exploratory, making it necessary for data analysts to have guidance when making critical decisions, such as selecting the number of market segments to extract. Cluster indices are a common method for obtaining this guidance. There are two types of cluster indices: internal and external. Internal cluster indices use information from a single segmentation solution to offer guidance, while external cluster indices require additional input from another segmentation solution to measure the similarity between the two solutions. The Jaccard index, Rand index, and adjusted Rand index are commonly used measures of similarity. Repeated calculations leading to similar market segments indicate that segments are extracted in a stable way.

Internal Cluster Indices

Internal cluster indices is used in market segmentation, which is a technique used by businesses to divide customers into groups based on similar characteristics. These indices rely on distance measures between observations or groups of observations to answer two main questions: (1) how compact are the market segments? and (2) how well-separated are the different market segments? Solutions for market segmentation can come from hierarchical, partitioning, or model-based clustering methods.

One simple internal cluster index that measures the compactness of clusters involves calculating the sum of distances between each segment member and their segment representative. The sum of within-cluster distances Wk for a segmentation solution with k segments can be determined by summing the distances of each segment. This method is used in the k-means algorithm, where the sum of within-cluster distances Wk decreases monotonically with increasing numbers of segments k extracted from the data.

External Cluster Indices

External cluster indices evaluate market segmentation solutions using additional external information. These external pieces of information can range from the true segment structure (if known) to a repeated calculation using a different clustering algorithm on the same data or on a variation of the original data. Label switching is a problem when comparing two segmentation solutions, and the Jaccard and Rand indices have been proposed as similarity measures.

However, these indices have the problem that absolute values are difficult to interpret because minimum values depend on the size of the market segments contained in the solution. To solve this problem, Hubert and Arabie proposed a general correction for agreement by chance given segment sizes, which can be applied to any external cluster index. The adjusted Rand index is a result of applying this correction to the Rand index. Function comPart() from package flexclust in R computes the Jaccard index, the Rand index, and the adjusted Rand index.

Gorge Plots

Gorge plot is a method to assess the separation of market segments by examining the distances between consumers and segment representatives. Similarity values are calculated based on these distances and can be visualized using gorge plots, silhouette plots, or shadow plots. The article emphasizes the importance of a well-defined gorge plot, which shows a clear separation of consumers into their respective market segments. It is suggested to conduct stability analysis to overcome the disadvantages of generating and inspecting a large number of gorge plots.

Global Stability Analysis

Global Stability Analysis is an alternative approach to analyzing data structures that can be used for distance and model-based segment extraction techniques, based on resampling methods. These methods generate new data sets to extract several segmentation solutions and compare the stability of these solutions across repeated calculations. The most stable segmentation solution is chosen.

Three possible scenarios for consumer data: natural segments exist, the data is entirely unstructured, or the data is in the middle of the previous two scenarios. In the case of natural segments, the resulting segments can be used for long-term strategic planning and customizing the marketing mix. In the case of unstructured data, managerially useful market segments must be constructed, and the data analyst offers potentially interesting segmentation solutions to the user. In the case of reproducible segmentation, the existing structure can be used to extract artificially created segments that re-emerge across repeated calculations.

Global stability analysis is suggested to determine the most suitable number of segments to extract from the data. Global stability analysis generates new data sets using bootstrapping techniques, which can be used to compute replicate segmentation solutions for different numbers of segments.

Segment Level Stability Analysis

Choosing the best overall segmentation solution doesn't always mean it contains the best market segment. Relying solely on global stability analysis could result in selecting a segmentation solution with overall stability, but without any highly stable individual segment. It's important to evaluate both the global stability and the stability of individual segments in alternative market segmentation solutions to avoid discarding potential valuable segments. In the end, organizations usually only need one target segment.

Segment Level Stability Within Solutions (SLSW)

Dolnicar and Leisch (2017) propose an approach to assess market segmentation solutions based on the concept of segment level stability within solutions (SLSW). The SLSW measures how often a market segment with the same characteristics is identified across a number of repeated calculations of segmentation solutions with the same number of segments. This approach helps to detect one highly stable segment in a segmentation solution where several or even all other segments are unstable. Hennig (2007) recommends drawing several bootstrap samples, calculating segmentation solutions independently for each of those bootstrap samples, and then determining the maximum agreement across all repeated calculations using the Jaccard index to assess SLSW.

Overall, Dolnicar and Leisch's approach is valuable because it helps prevent an overall bad market segmentation solution from being discarded, as it allows for the detection of one highly stable segment, which could be a potentially attractive niche market, in a segmentation solution where several or even all other segments are unstable.

Segment Level Stability Across Solutions (SLSA)

The second criterion of stability at segment level proposed by Dolnicar and Leisch (2017), called segment level stability across solutions (SLSA). The criterion aims to determine the recurrence of a market segment across different market segmentation solutions containing varying numbers of segments. High values of SLSA indicate natural market segments that exist in the data and are not artificially created, which are more attractive to organizations because no managerial judgment is required in their identification. The article explains that SLSA can be calculated with any algorithm that extracts segments, and it reflects the fact that a sequence of nested partitions is created for hierarchical clustering. However, for partitioning methods like k-means, k-medians, neural gas, and finite mixture models, the segment labels are random and depend on the random initialization of the extraction algorithm. Therefore, to compare segmentation solutions, it is necessary to identify which segments in each solution are similar and assign consistent labels. Dolnicar and Leisch (2017) propose an algorithm to renumber series of partitions, which is implemented in the function relabel() in package flexclust.

The usefulness of SLSA in guiding the data analyst using an artificial mobile phone dataset. The SLSA plot shows the development of each segment across segmentation solutions with different numbers of segments, where each column in the plot represents a segmentation solution with a specific number of segments.

6 Step VI : Profiling Segments:

6.1Identifying Key Characteristics of Market Segments:

The profiling step is necessary for data-driven market segmentation, but not for commonsense segmentation. Profiling involves identifying defining characteristics of market segments with respect to segmentation variables. It is important to inspect alternative segmentation solutions, especially if no natural segments exist in the data. Good profiling is critical for correct interpretation of the resulting segments, which is important for making good strategic marketing decisions.

Marketing managers often face in interpreting data-driven market segmentation solutions. Studies show that a significant percentage of marketing managers struggle to understand such solutions, with 65% reporting difficulties interpreting them correctly. Furthermore, 71% of the managers feel that segmentation analysis is like a black box. The article provides quotes from marketing managers illustrating how market segmentation results are often presented to them. Some of these are :

- . . . as a long report that usually contradicts the results
- . . . rarely with a clear Executive Summary
- . . . in a rushed slap hazard fashion with the attitude that ‘leave the details to us’ ...
- The result is usually arranged in numbers and percentages across a few (up to say 10) variables, but mostly insufficiently conclusive.
- ...report or spreadsheet...report with percentages
- . . . often meaningless information • In a PowerPoint presentation with a slick handout

1.1Traditional Approaches to Profiling Market Segments:

Data-driven segmentation solutions are usually presented to users (clients, managers) in one of two ways: (1) as high level summaries simplifying segment characteristics to a point where they are misleadingly trivial, or (2) as large tables that provide, for each segment, exact percentages for each segmentation variable. Such tables are hard to interpret, and it is virtually impossible to get a quick overview of the key insights.

Sometimes – to deal with the size of this task – information is provided about the statistical significance of the difference between segments for each of the segmentation variables. This approach, however, is not statistically correct. Segment membership is directly derived from the segmentation variables, and segments are created in a way that makes them maximally different, thus not allowing to use standard statistical tests to assess the significance of differences.

6.2Segment Profiling with Visualisations:

The importance of using graphics in data-driven market segmentation solutions is very handy. Currently, these solutions are presented using either highly simplified or complex tabular representations, which do not make optimal use of graphics. However, graphics play a crucial role in exploratory statistical analysis, such as cluster analysis, as they provide insights into the complex relationships between variables. Additionally, in times of big data, visualization offers a simple way of monitoring developments over time.

The article highlights the recommendations of McDonald and Dunbar and Lilien and Rangaswamy to use visualization techniques to make the results of a market segmentation analysis easier to interpret.

At last we can say that visualizations are useful in the data-driven market segmentation process to inspect one or more segments in detail and to assess the usefulness of a market segmentation solution. The process of segmenting data leads to a large number of alternative solutions, and selecting one of the possible solutions is a critical decision. Visualizations of solutions assist the data analyst and user with this task. Therefore, incorporating graphics in data-driven market segmentation solutions can lead to better insights and decision-making.

6.3Identifying Defining Characteristics of Market Segments :

A good way to understand the defining characteristics of each segment is to produce a segment profile plot. The segment profile plot shows – for all segmentation variables – how each market segment differs from the overall sample.

Segmentation variables do not have to be displayed in the order they appear in the data set in figures and tables. If variables in the data set have a meaningful order, that order should be preserved. If, on the other hand, the order of variables is independent. It is beneficial to rearrange variables in order to improve visualisations. We can use colors and markers for our convenient explanation. As example:

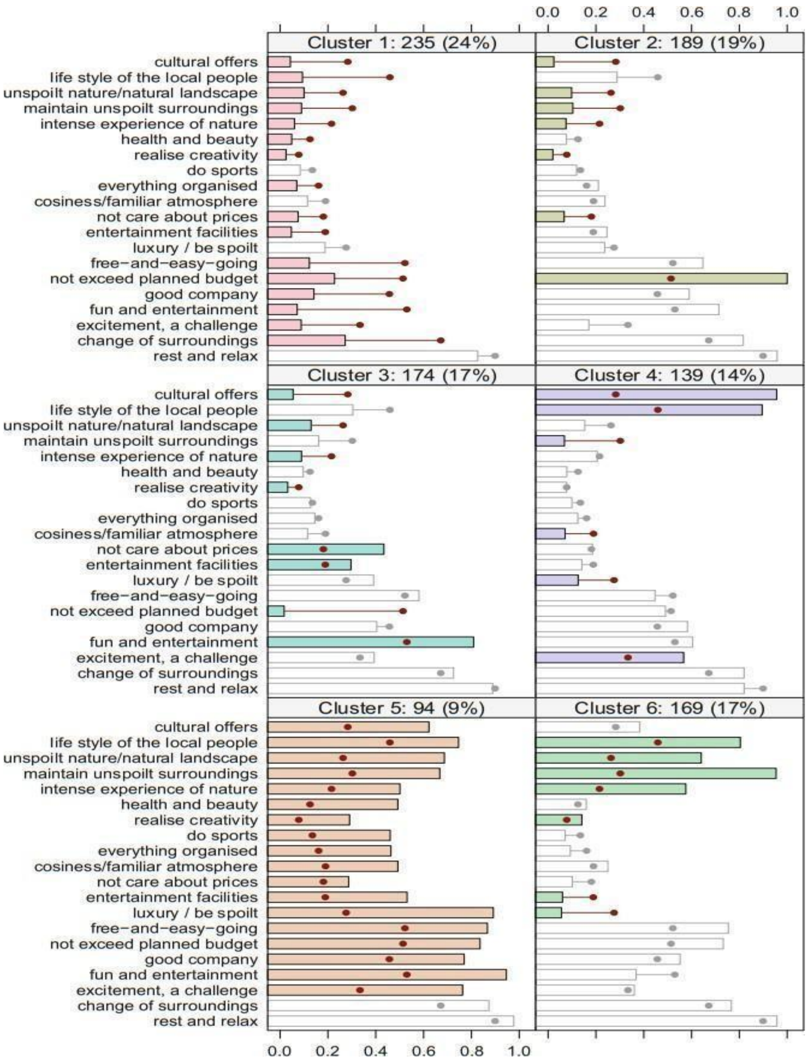


Fig 4 : Segment profile plot for the six-segment solution of the Australian travel motives data set

6.4Assessing Segment Separation:

A segment separation plot is used to visualize segment separation, depicting the overlap of segments across all relevant dimensions of the data space. While segment separation plots are simple with a low number of segmentation variables, they become complex as the number of variables increases. However, even in complex situations, segment separation plots provide a quick overview of the data and segmentation solution for data analysts and users.

The plots below is showing the cluster of data of some arbitrary dataset.

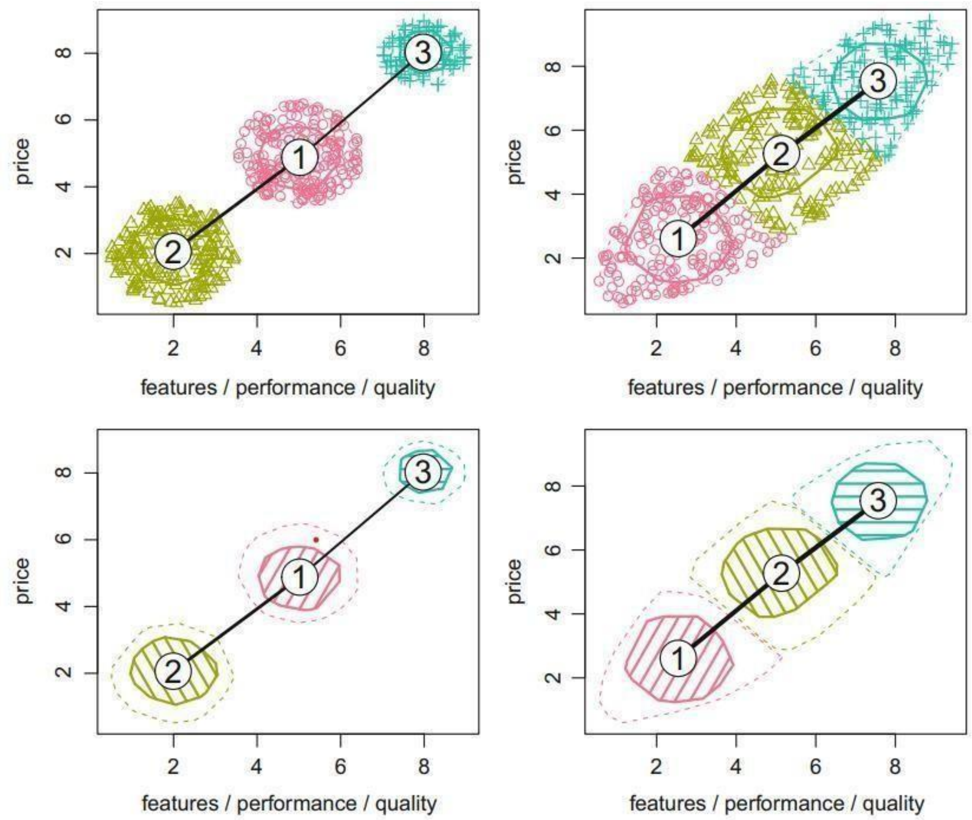


Fig 5 : Segment separation plot including observations (first row) and not including observations (second row) for two artificial data sets: three natural, well-separated clusters (left column); one elliptic cluster (right column)

The excerpt describes the segment separation plot, which is used to visualize the overlap of segments in a data set. The plot consists of a scatter plot of the observations colored by segment membership, along with the projected cluster hulls and a neighborhood graph that indicates the similarity between segments. The plot is demonstrated using two artificial data sets that contain three distinct segments and an elliptic data structure. In the plot, the color of the observations indicates true segment membership, and the different cluster hulls indicate the shape and spread of the true segments. The dashed cluster hulls contain all observations, while the solid cluster hulls contain approximately half of the observations. The neighborhood graphs, represented by black lines with numbered nodes, indicate similarity between segments. The width of the black line is thicker if more observations have these two segment centers as their closest segment centers. The excerpt also notes that in cases where there are high-dimensional data sets, the data may need to be projected onto a smaller number of dimensions to create a segment separation plot using techniques like principal components analysis or separation maximization. The following figure showing some overlapping segments which are usually hard to interpret. But using the PCA we can partially interpret those segment.

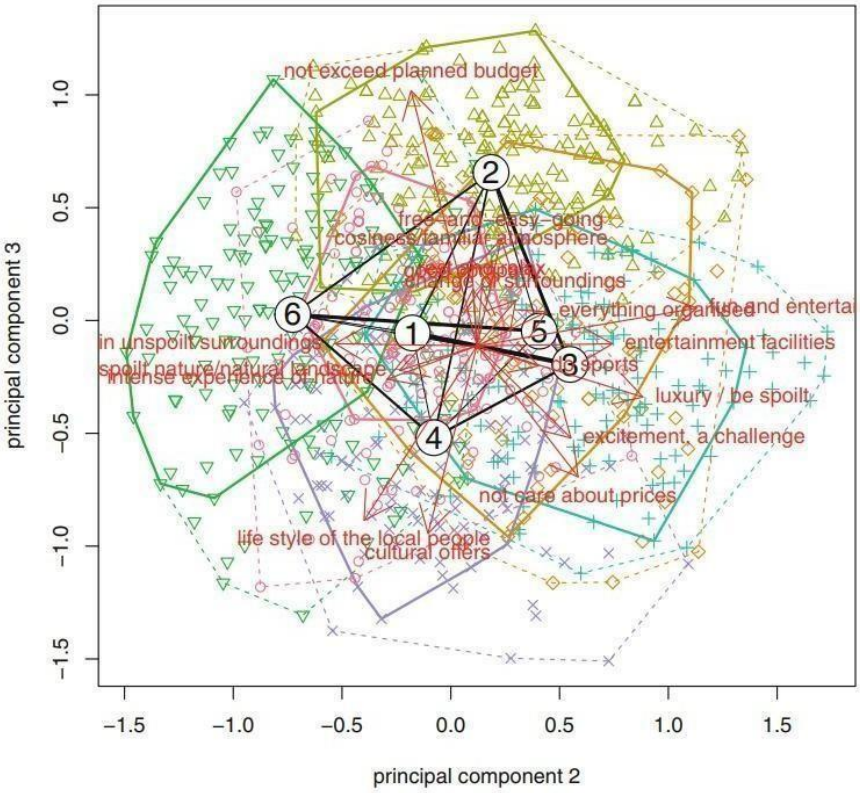


Fig 6 : Segment separation plot using principal components 2 and 3 for the Australian travel motives data set

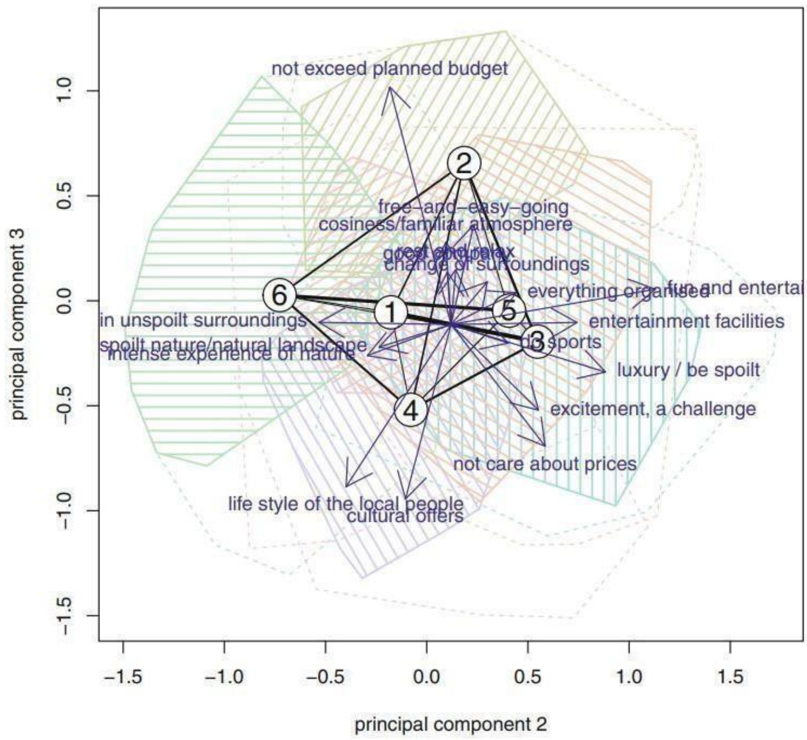


Fig 7 : Segment separation plot using principal components 2 and 3 for the Australian travel motives data set without observations

Each segment separation plot only visualises one possible projection. So, for example, the fact that segments 1 and 5 in this particular projection overlap with other segments does not mean that these segments overlap in all projections. However, the fact that segments 6 and 3 are well-separated in this projection does allow the conclusion – based on this single projection only – that they represent distinctly different tourists in terms of the travel motives.

Step 7: Describing Segments

- Developing a Complete Picture of Market Segments

The marketing literature traditionally relies on statistical testing, and tabular presentations of differences in descriptor variables. Visualisations make segment description more user-friendly.

- Using Visualizations to Describe Market Segments

Graphical statistics to describe market segments has two key advantages: simplifying interpretation and integrating statistical significance, and conveying the essence of marketing research results.

Metric Descriptor Variables

Conditional plots demonstrate that respondents in the acquiescence section tend to agree with survey questions in general and are more likely to agree when questioned about their moral responsibility to protect the environment.

The most important idea is that members of the acquiescence segment have an overall tendency to express agreement with survey questions, and are more likely to express agreement when asked about their moral obligation to protect the environment.

Testing for Segment Differences in Descriptor Variables

The $\chi 2$-test rejects the null hypothesis of independence if the p-value is smaller than 0.05, so a mosaic plot is used to identify the reason for rejection. ANOVA is used to test for significant differences in mean moral obligation values across market segments. The analysis of variance performs an F-test to compare the weighted variance between market segment means with the variance within market segments. Small values support the null hypothesis that segment means are the same, but the analysis of variance does not identify the differing segments. P-values need to be adjusted for multiple testing when assessing a single hypothesis, such as that all segment means are the same.

Predicting Segments from Descriptor Variables

Regression analysis is the basis of prediction models, which test differences in all descriptor variables simultaneously to determine how well members of a market segment can be identified. It is very essential for accurate outcome .

Segment membership C6 is a categorical variable with six categories, and the formula interface fits a regression coefficient for each category. Without an intercept, each estimated coefficient is equal to the mean age in the segment.

Binary Logistic Regression :

$$g(u) = n = \log(u)/\log(1-u)$$

The binomial distribution is a generalization of the Bernoulli distribution if the variable y does not only take values 0 and 1, but represents the number of successes out of a number of independent Bernoulli distributed trials with the same success probability μ. The regression coefficients in a linear regression model indicate how much the mean value of the dependent variable changes if this independent variable changes while others remain unchanged. The coefficient for AGE indicates that the log odds for being in segment 3 are 0.008 lower for tourists who are one year older. The independent variable OBLIGATION2 is a categorical variable with four different levels. The regression coefficients for this variable indicate the change in log odds between the other categories and the lowest category Q1. Function all Effects calculates the predicted values for different levels of the independent variable keeping other independent variables constant at their average value. The predicted values are the probabilities of being in the segment 3. We plot the estimated probabilities to allow for easy inspection.

Multinomial Logistic Regression

In R, function multinorm() from package fits a multinomial logistic regression. The regression coefficients are arranged in matrix form. Each row contains the regression coefficients for one category of the dependent variable. Each column contains the regression coefficients for one effect of an independent variable.

Tree-Based Methods

Classification and regression trees (CARTs) are an alternative modelling approach for predicting a binary or categorical dependent variable given a set of independent variables. They use a stepwise procedure to fit the model, splitting consumers into groups based on one independent variable.

The resulting tree shows the nodes that emerge from each splitting step, with the root node containing all consumers and terminal nodes that are not split further. Segment membership can be predicted based on the segment memberships of consumers contained in the terminal node. The output of the fitted classification tree shows that consumers with a Vacation. Node 4 contains 490 respondents, 81% of whom are not in segment 3, 19% are, and most of them are in node 5. The proportion of respondents in node 2 who belong to segment 3 is shown at the bottom of the stacked bar chart. The output shows that the first splitting variable is the categorical variable indicating moral obligation (OBLIGATION2).

This variable splits the root node 1 into nodes 2 and 5. Node 3 is a terminal node and contains 481 respondents. Node 5 contains respondents with a moral obligation value of 47 or less, and a moral obligation category value of Q4. Node 6 contains 203 respondents and 67% are not from segment 6. Node 6 contains 203 respondents and 67% are not from segment 6. Node 7 contains 30 consumers and 57% do not belong to segment 5. Most of the plot is the same as for the classification tree with the binary dependent variable, except for the bar charts at the bottom.

Step 7

Predicting Segments from Descriptor Variables

The regression analysis can be used to predict market segments by using segment membership as the dependent variable and descriptor variables as the independent variables. The linear regression model is used as the basis for prediction models, assuming that the dependent variable can be predicted using independent variables or regressors. Regression models differ in terms of the function, distribution, and deviations between the dependent variable and the independent variables. The text provides examples of how to fit a linear regression model in R for age in dependence of segment membership using the lm() function. The output indicates which descriptor variables are critical to the identification of segment membership and shows the regression coefficients for each category. The generalised linear models can accommodate a wider range of distributions for the dependent variable and introduces a link function to transform the mean value of y to an unlimited range indicated by η.

Binary Logistic Regression

Binary logistic regression is a statistical model used to analyze the relationship between a binary response variable (i.e., a variable with two possible outcomes) and one or more predictor variables The use of generalized linear models (GLMs) for binary data, specifically the Bernoulli distribution with success probability μ and the logit link function that maps μ onto (-∞,∞). The function glm() in R is used to fit GLMs, and the Bernoulli distribution with logit link is specified with family = binomial(link = "logit"). The passage describes the fitting of a binary logistic regression model to predict the likelihood of a consumer being in a certain segment, given their age and moral obligation score. The dependent variable is a binary indicator of belonging to the segment, and the two independent variables are AGE and OBLIGATION2. The output of the model includes regression coefficients, degrees of freedom, null deviance, residual deviance, and AIC.

To simplify the interpretation of the coefficients, the package effects in R is used to calculate predicted values for different levels of the independent variables, with other independent variables held constant at their average value. The predicted values are plotted to show how the predicted probability of being in the segment changes with age and moral obligation categories. The plot shows non-linear changes that depend on the values of other independent variables.

Multinomial Logistic Regression

To perform multinomial logistic regression in R. This method is used to predict categorical dependent variables that follow a multinomial distribution, which is common in market segmentation analysis. The multinom() function from the nnet package is used to fit the model, and a formula and data frame are used to specify the model. The coefficients obtained indicate the change in log odds for each independent variable, and the summary() function returns both the coefficients and their standard errors. The Anova() function is used to assess the significance of each variable in the model, and the step() function can be used for model selection. The predicted segment membership can be compared to the observed segment membership using a mosaic plot, and the distribution of predicted probabilities for each segment can be analyzed using parallel boxplots.

Tree-Based Methods

Classification and Regression Trees (CARTs) is used for predicting a binary or categorical dependent variable using independent variables. CARTs are advantageous due to their ability to perform variable selection, ease of interpretation, and incorporation of interaction effects. However, their results can be unstable.

The tree approach involves splitting consumers into groups based on one independent variable, with the goal of making the resulting groups as pure as possible with respect to the dependent variable. The resulting tree shows the nodes that emerge from each splitting step, with the root node containing all consumers and the terminal nodes being the final prediction points.

Tree constructing algorithms differ in various aspects, including splits, selection criteria, and stopping criteria. The article describes the packages available for implementing these algorithms, such as rpart and partykit.The ctree() function from the partykit package fits a conditional inference tree, which is demonstrated using the Australian travel motives dataset. The output of the fitted classification tree is described, including the root node and the split into two nodes based on the VACATION.BEHAVIOUR independent variable.The tree predicts that consumers in node 2 are not in segment 3, while those in node 5 have an 11% chance of being in segment 3.

Step 8: Selecting the Target Segment(s)

1) The Targeting Decision

Step 8 in market segmentation is the point at which the target segment(s) for a product or service are selected. It is a strategic marketing decision that can significantly impact an organisation's future performance. The knock-out criteria for market segments, identified in Step 2, are reviewed to ensure that only suitable segments are considered. Informed by all the insights gained during the entire market segmentation analysis, the time has come to commit. Of the many available market segments, one or a small number have to be chosen and declared target segments. This critical step builds on the segments extracted in Step 5, profiled in Step 6, and described in Step 7, as well as on the segment attractiveness criteria selected and weighted in Step 2. The process requires the involvement of the segmentation team and the advisory committee because decisions made at this point will result in a long-term organisational commitment affecting all organisational units. The two key questions that need to be answered in this step are:

1) Which of the market segments would the organisation most like to target? Which segment would the organisation like to commit to?
2) Which of the organisations offering the same product would each of the segments most like to buy from? How likely is it that our organisation would be chosen? How likely is it that each segment would commit to us?

Answering these two questions forms the basis of the target segment decision.

2) Market Segment Evaluation

A decision matrix, such as the Boston matrix or market attractivenessbusiness strength matrix, is used to visualise relative segment attractiveness and relative organisational competitiveness for each market segment. It discusses the use of decision matrices to evaluate alternative market segments and select one or a small number for targeting. The decision matrix visualizes relative segment attractiveness and relative organizational competitiveness for each market segment, with the two criteria plotted along the axes covering two dimensions: segment attractiveness and relative organizational competitiveness specific to each of the segments. It explains how to calculate the values for each axis based on agreed-upon criteria, weighting, and rating of each market segment and how to plot the results as circles with the size of the circles reflecting another criterion of choice that is relevant to segment selection, such as contribution to turnover or loyalty. There is no single best measure of segment attractiveness or relative organizational competitiveness and that the ideal target segment is specified in Step 2 of the market segmentation analysis, resulting in a number of criteria of segment attractiveness and weights quantifying how much impact each of these criteria has on the total value of segment attractiveness. The market segmentation team should decide which variation of the decision matrix best assists with decision-making.

Customising the Marketing Mix:

The marketers have at their disposals 12 ingredients:

- Product planning
- Packaging
- Physical handling
- Distribution channels
- Pricing
- Personal selling
- Branding
- Display
- Advertising
- Promotions
- Servicing
- Fact finding and analysis

The marketing mix consist of:

- **Product**
- **Price**
- **Promotion**
- **Place**

1. Product:

- An organisation needs to make when developing the product dimension of the marketing mix, is to specify the product in view of customer needs.
- Marketing mix decisions that fall under the product dimension are: **Naming the product**, **packaging it**, **offering or not offering warranties**, and **after sales support services.**

2. Price:

- The price dimension of the marketing mix include **setting the price for a product,** and **deciding on discounts** to be offered.

3. Place:

- The place dimension of the marketing mix is how to distribute the product to the customers.
- This includes answering questions such as: **should the product be made available for purchase online or offline only or both**; **should the manufacturer sell directly to customers**; or **should a wholesaler** or a retailer or both be used.

4. Promotion:

- The promotion decisions that need to be made when designing a marketing mix include: **developing an advertising message that will resonate with the target market**, and **identifying the most effective way of communicating this message.**

McDonalds Case Study

Step 1: Deciding the segment

Basically their are two segments: mass marketing and differentiated marketing strategy.Mass marketing strategy can be defined as it caters to the entire market and that there is no need to understand systematic differences across market segments. Differentiated marketing strategy can be defined that it takes the position in investigating systematic heterogenity among consumers.

Step 2: Specifying the ideal target segment

The knock-out criteria for the target segment will be either they are homogeneous or distinct. Some different forms will be the strengths of McDonalds, identifiable and reachable. The segments attractiveness can be judged by the positive perception of McDonalds.

Step 3: Collecting Data

The dataset contains attributes such as YUMMY, CONVENIENT, SPICY, FATTENING, GREASY, FAST, CHEAP, TASTY, EXPENSIVE,
HEALTHY and DISGUISTING. The responses are in the binary from ie. either Yes(1) or No(0).

Step 4: Exploring Data

a. Data Cleaning: Check if all values have been recorded correctly, consistent labels for the levels of categorical variables have been used.

b. Pre-Processing: a) Categorical Variables -Two procedures – I. Merging levels of categorical variables before further analysis II. Converting categorical variables to numeric ones b) Numeric variables-
The range of values of a segmentation variable affects its relative influence in distance-based methods of segment extraction. To balance the influence of segmentation variables on segmentation results, variables can be standardised. Standardising variables means transforming them in a way that puts them on a common scale. The default standardisation method in statistics subtracts the empirical mean x¯ and divides by the empirical standard deviation s. Alternative standardisation methods may be required if the data contains observations located very far away from most of the data (outliers).

c. Principal components analysis (PCA) transforms a multivariate data set containing metric variables to a new data set with variables – referred to as principal components – which are uncorrelated and ordered by importance. The PCAs are ordered by their variability. Principal components analysis basically keeps the data space unchanged, but looks at it from a different angle. Principal components analysis works off the covariance or correlation matrix of several numeric variables. If all variables are measured on the same scale, and have similar data ranges, it is not important which one to use. If the data ranges are different, the correlation matrix should be used. If the first few principal components do not explain much of the variance indicates that all the original items are needed as segmentation variables. They are not redundant. They all contribute valuable information.