MARKET SEGMENTATION ANALYSIS

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Contents

Introduction

The book "***Market Segmentation Analysis - Understanding It, Doing It, and Making It Useful***" is written by Sara Dolnicar, Bettina Grün, and Friedrich Leisch. It is published by Springer Open Access under the Creative Commons Attribution 4.0 International License.

The book offers something for everyone working with market segmentation: practical guidance for users of market segmentation solutions; organizational guidance on implementation issues; guidance for market researchers in charge of collecting suitable data; and guidance for data analysts with respect to the technical and statistical aspects of market segmentation analysis. Even market segmentation experts will find something new, including a vast array of useful visualization techniques that make the interpretation of market segments and selection of target segments easier.

The book talks the reader through every single step, every single potential pitfall, and every single decision that needs to be made to ensure market segmentation analysis is conducted as well as possible.

Market segmentation is the practice of dividing your target market into approachable groups. Market segmentation creates subsets of a market based on demographics, needs, priorities, common interests, and other psychographic or behavioral criteria used to better understand the target audience.

Link to the book pdf:
https://github.com/DivyaGazinkar/Machine-Learning-Internship-2023/blob/main/Market%20Segmentation%20and%20Case%20Study/Book/Market_Segmentation_Analysis.pdf

Next is the summary of the **Ten Steps of Market Segmentation Analysis**

Ten Steps of Market Segmentation Analysis

Step 1: Deciding (not) to Segment

In this step, the authors discuss the implications of committing to a market segmentation strategy and the potential barriers that can arise during its implementation.

1.1 Implications of Committing to Market Segmentation:

Before engaging in market segmentation analysis, it's essential to understand the long-term commitment it requires. Market segmentation is a strategic decision that involves substantial changes and investments. The commitment to this strategy should be akin to a marriage, not a temporary arrangement. Research, surveys, package designs, advertisements, and communication costs must be considered. The decision to pursue segmentation should be profitable enough to justify its costs.
Given the significant organizational commitment required, the decision to explore market segmentation should be made at the highest executive level. Communication and reinforcement of this decision across all levels and units of the organization are vital.

1.2 Implementation Barriers:

Senior Management: Lack of leadership, commitment, and resources from senior management can undermine the process.
Organizational Culture: Factors like resistance to change, lack of consumer orientation, and poor communication can hinder implementation.
Lack of Training: Lack of understanding among senior management and the segmentation team can lead to failure.
Formal Marketing Function: Organizations need a formal marketing function or experts for successful implementation.
Objective Restrictions: Lack of financial resources, inability to make required changes, and process-related issues can pose obstacles.

Step 2: Specifying the Ideal Target Segment

2.1 Segment Evaluation Criteria

The third layer of analysis in market segmentation greatly relies on user input. To achieve valuable outcomes for the organization, it's crucial to engage users not just in the initial briefing or final marketing mix development, but throughout various stages, closely integrated with the technical aspects of segmentation analysis.

Once an organization commits to exploring the value of segmentation in Step 1, a substantial contribution is made in Step 2. Although abstract, this contribution significantly influences subsequent steps, especially in Steps 3 (data collection) and 8 (selecting target segments). In Step 2, the organization establishes two criteria for evaluating segments.

One of these sets, called knock-out criteria, covers essential, non-negotiable segment characteristics that the organization deems suitable for targeting. The second set, called attractiveness criteria, serves to gauge the relative desirability of the remaining market segments that meet the knock-out criteria.

2.2 Knock-Out Criteria

These criteria serve to determine if the market segments emerging from the analysis are eligible for assessment using segment attractiveness criteria.

These criteria encompass several essential considerations:

Homogeneity: Members within a segment should share similarities.
Distinctness: Members of a segment must be notably different from other segments.
Size: A segment should have a sufficient consumer base, justifying customization investments.
Alignment with Organizational Strengths: The organization must be capable of meeting segment needs.
Identifiability: The segment's members should be identifiable within the market.
Reachability: Communication channels to the segment should be accessible for tailored marketing.
Understanding these criteria is essential for senior management, the segmentation team, and the advisory committee. While most criteria are self-explanatory, some might necessitate further specification. For instance, while size is a decisive criterion, determining the minimum viable target segment size might require specification.

2.3 Attractiveness criteria

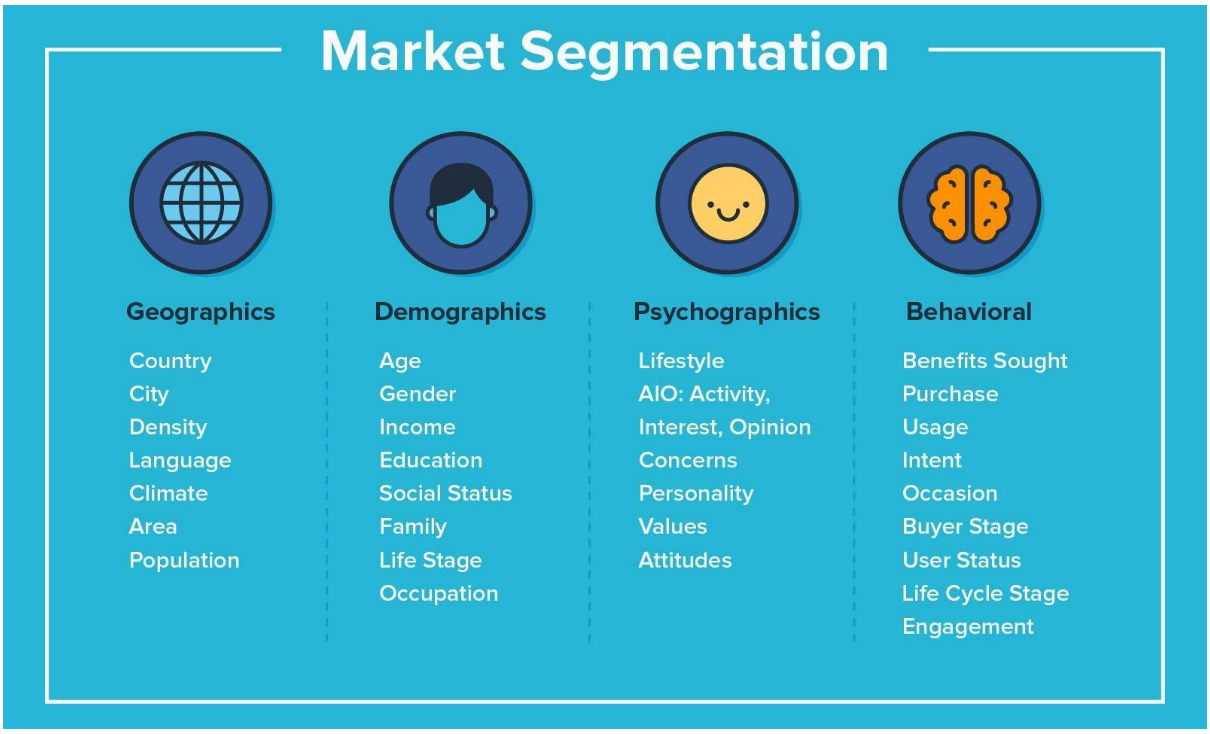
The concept of attractiveness criteria is dynamic and non-binary. Rather than a simple compliance or non-compliance assessment, each market segment is assigned a rating of attractiveness based on specific criteria. The culmination of these attractiveness ratings across all criteria determines whether a market segment is chosen as a target segment during Step 8 of the market segmentation analysis

Step 3: Collecting Data

The concept of market segmentation relies on empirical data to identify and categorize market segments. This data-driven approach employs segmentation variables to divide a sample into distinct segments. The term "segmentation variable" refers to a specific characteristic measured in the empirical data used to separate the sample into segments. In common sense segmentation, a single characteristic, such as gender, is typically used as the segmentation variable. This approach results in segments like men and women.

Other personal characteristics, such as age, vacation frequency, and preferences, act as descriptor variables, describing the segments in detail. These descriptors aid in developing effective marketing strategies tailored to each segment's needs. The contrast between commonsense and data-driven segmentation lies in the use of multiple segmentation variables in the latter, enabling the identification of naturally occurring or artificially created segments beneficial to the organization.

Geographic, sociodemographic, psychographic, and behavioral are common segmentation criteria.



Geographic segmentation is based on location, sociodemographic on factors like age and income, psychographic on psychological aspects like interests and preferences, and behavioral on reported behaviors like past purchases.

While geographic and sociodemographic criteria are straightforward to implement, they may not always capture the underlying reasons for consumer behavior. Psychographic criteria delve deeper into motivations, while behavioral criteria directly use actual behavior for segment extraction. Survey data is commonly used for market segmentation but is susceptible to biases and response styles, which can impact the quality of segmentation outcomes. Careful selection of variables and response options, as well as mitigation of response styles, are crucial for effective segmentation analysis.

The significance of sample size in market segmentation analysis is illustrated, revealing the challenges that arise from inadequate sample sizes. The effectiveness of segmentation algorithms heavily depends on sample size, impacting the ability to determine the correct number and nature of market segments.

Internal data sources are increasingly utilized for segmentation analysis, containing actual consumer behavior data like scanner data from stores, booking data from loyalty programs, and online purchases. The strength of such data lies in their authenticity and ease of access, yet there's a risk of bias from over-representing existing customers and lacking information on potential future customers.

Experimental data from field or laboratory experiments, such as consumer responses to advertisements, and data from choice experiments or conjoint analyses, where preferences for different product attributes are studied, can also serve as sources for segmentation analysis. These alternative data sources offer unique insights into consumer behavior and preferences.

Step 4: Exploring Data

4.1 A First Glimpse at the Data

After data collection, exploratory data analysis cleans and – if necessary – preprocesses the data. This exploration stage also offers guidance on the most suitable algorithm for extracting meaningful market segments.

At a more technical level, data exploration helps to

- identify the measurement levels of the variables;
- investigate the univariate distributions of each of the variables; and
- Assess dependency structures between variables.

In addition, data may need to be pre-processed and prepared so it can be used as input for different segmentation algorithms. Results from the data exploration stage provide insights into the suitability of different segmentation methods for extracting market segments.

4.2 Data Cleaning

The first step before commencing data analysis is to clean the data. This includes checking if all values have been recorded correctly and if consistent labels for the levels of categorical variables have been used.

4.3 Descriptive Analysis

Descriptive numeric and graphic representations provide insights into the data. Statistical software packages offer a wide variety of tools for descriptive analysis. Helpful graphical methods for numeric data are histograms, boxplots, and scatter plots. Bar plots of frequency counts are useful for the visualization of categorical variables. Mosaic plots illustrate the association of multiple categorical variables.

4.4 Pre-Processing

4.4.1 Categorical Variables

Two pre-processing procedures are often used for categorical variables. One is merging levels of categorical variables before further analysis, the other one is converting categorical variables to numeric ones, if it makes sense to do so. Merging levels of categorical variables is useful if the original categories are too differentiated (too many)

4.4.2 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 standardized. Standardizing variables means transforming them in a way that puts them on a common scale.
The default standardization method in statistics subtracts the empirical mean x¯ and divides it by the empirical standard deviation

4.3 Principal Components Analysis

Principal components analysis (PCA) transforms a multivariate data set containing metric variables to a new data set with variables – referred to as principal components – that are uncorrelated and ordered by importance. The first variable (principle component) contains most of the variability, the second principle component contains the second most variability, and so on. After transformation, observations (consumers) still have the same relative positions to one another, and the dimensionality of the new data set is the same because principal components analysis generates as many new variables as there were old ones. Principal components analysis basically keeps the data space unchanged but looks at it from a different angle.

Step 5: Extracting Segments

5.1 Distance-Based Methods

Market segmentation aims at grouping consumers into groups with similar needs or behavior. Different distance measures can be used to determine the similarity or dissimilarity between the consumers.

5.1.1 Distance Measures

Euclidean distance calculates the straight-line distance between two points in a multidimensional space. It considers all dimensions of the vectors and calculates the square root of the sum of squared differences between corresponding elements.
Manhattan distance calculates the distance between two points by summing the absolute differences between corresponding elements. It also considers all dimensions of the vectors.
Asymmetric binary distance measure is specific to binary vectors, where elements are either 0 or 1. It calculates the proportion of common 1's overall dimensions where at least one vector contains a 1.

5.2.2 Hierarchical Methods

Hierarchical clustering is an exploratory technique that offers a structured approach to grouping data. It provides a sequence of nested partitions. There are two types of hierarchical methods divisive and agglomerative. In divisive hierarchical clustering, the process starts with the complete dataset and splits it into two segments. Each segment is then further split into two, and this process continues until each observation has its own segment. On the other hand, agglomerative hierarchical clustering takes the opposite approach. It starts with each observation representing its own segment (singleton clusters) and then gradually merges the closest segments until the entire dataset forms one large segment. This can be performed using different distance measures and linkage methods. Dendrograms are commonly used to visualize the clustering results. Dendrograms visualize the hierarchy of segments formed at each step of the clustering process, with the height of the branches indicating the distance between clusters. Dendrograms can be used as a guide to select the number of market segments, although they may not always provide clear guidance in consumer data analysis due to the complexity of the data.

5.2.3 Partitioning Methods

Hierarchical clustering methods are often used for the analysis of small data sets with up to a few hundred observations. They create a hierarchical structure of clusters, represented by a dendrogram. However, for larger data sets, dendrograms become difficult to read, and the pairwise distance matrix may not fit into computer memory. For larger data sets with more than 1000 observations, partitioning clustering methods are more suitable. These methods aim to create a single partition of the data into segments rather than a nested sequence of partitions. One popular partitioning method is k-means clustering, which divides the data into subsets or segments based on their similarity.

k-Means and k-Centroid Clustering

K-means clustering is the most commonly used distance-based partitioning clustering algorithm. Using random consumers from the data sets as starting points, the standard k-means clustering algorithm iteratively assigns all consumers to the cluster centres (centroids, segment representatives), and adjusts the location of the cluster centres until cluster centres do not change anymore. Standard k-means clustering uses the squared Euclidean distance. Generalizations using other distances are also referred to as k-centroid clustering. The k-means algorithm involves several steps:

1. Specify the desired number of segments, denoted as k.
2. Randomly select k observations as initial cluster centroids.
3. Assign each observation to the closest cluster centroid to form an initial partition.
4. . Recompute the cluster centroids based on the current partition.
5. Repeat steps 3 and 4 until convergence or a maximum number of iterations is reached.

Improved k-means:
In market segmentation analysis, various algorithms and methods can be used to refine and improve the k-means clustering algorithm. One common improvement is to initialize the k-means algorithm with smart starting values instead of randomly selecting consumers from the data set. The best starting points are those that effectively represent the data, with representatives that are close to their segment members. This approach helps avoid the problem of getting trapped in local optima.

Hard Competitive Learning:
This method differs from k-means in how segments are extracted. Instead of using all consumers in the data set at each iteration, hard competitive learning randomly selects one consumer and moves its closest segment representative towards it. This procedural difference can lead to different segmentation solutions compared to k-means, and it may find the globally optimal solution while k-means gets stuck in a local optimum.

Neural Gas and Topology Representing Networks:
Neural gas and topology representing networks are further extensions of hard competitive learning. Neural gas adjusts not only the closest representative but also the second closest representative towards the randomly selected consumer, with a smaller adjustment for the second closest. Topology representing networks counts how often each pair of segment representatives is closest and second closest to a randomly drawn consumer, creating a virtual map that represents the relationships between representatives.

Self-organizing maps:
Self-organizing maps are another variation of hard competitive learning that positions segment representatives on a regular grid. It uses a rectangular or hexagonal grid and adjusts the representatives based on the selected random consumer and its closest neighbours. The advantage of Self-organizing maps is that the numbering of market segments aligns with the grid, providing a structured output. However, the sum of distances between segment members and representatives can be larger compared to other clustering algorithms due to the restrictions imposed by the grid.

Neural Networks:
Neural networks, specifically auto-encoding neural networks, are a different approach to cluster analysis. They use a single hidden layer perceptron to learn the best representation of the data and predict the inputs as accurately as possible. The parameters connecting the hidden layer to the output layer can be interpreted as segment representatives, while the parameters connecting the input layer to the hidden layer indicate membership in different segments.

Hybrid Approaches:
Hybrid segmentation approaches aim to leverage the strengths of both hierarchical and partitioning algorithms. They begin with a partitioning algorithm for scalability, then transition to hierarchical clustering using reduced data to determine the appropriate number of segments. This combination allows for efficient segmentation of large datasets while enabling visualization and decision-making based on segment similarities.

Two-Step Clustering:
This process consists of two steps: a partitioning procedure followed by a hierarchical procedure. In the first step, a partitioning algorithm (such as k-means) is applied to the data to reduce its size and extract representative members from each cluster. The number of clusters extracted in this step is not crucial and can be larger than the actual number of segments sought. In the second step, a hierarchical cluster analysis is performed using the cluster centers and segment sizes obtained from the first step. The resulting dendrogram helps identify the number of market segments. Finally, the original data is linked to the segmentation solution derived from the hierarchical analysis.

Bagged Clustering:
Bagged clustering, on the other hand, combines hierarchical clustering and partitioning clustering with bootstrapping. It starts by creating multiple bootstrap samples from the original data set. Each bootstrap sample is then clustered using a partitioning algorithm. The cluster centroids obtained from these repeated partitioning analyses serve as the data set for the hierarchical clustering step. The final segmentation solution is determined by selecting a cut point in the dendrogram and assigning each observation to the closest market segment.

Model-Based Methods:
Model-based methods offer an alternative approach to market segmentation analysis by using finite mixture models. These models capture segment-specific characteristics and sizes, and various statistical techniques are employed to estimate the model parameters and assign consumers to segments.

Finite Mixtures of Distributions:
The finite mixture model is represented by a combination of segment-specific models, where each segment is associated with a set of parameters. The parameters, including segment sizes and segment-specific characteristics, need to be estimated using statistical estimation

techniques such as maximum likelihood estimation or Bayesian inference. To assign consumers to segments, probabilitiesof segment membership are calculated based on consumer information and the estimated parameter values. The segment with the highest probability is then assigned to the consumer.

Normal Distributions: A mixture of normal distributions is suitable for market segmentation when the segmentation variables are metric, such as money spent on different consumption categories, time spent engaging in different vacation activities, or body measurements for different clothing sizes. The multivariate normal distribution is suitable for modeling covariance between variables, and it commonly occurs in biological and business contexts. For instance, physical measurements on humans, such as height, arm length, leg length, or foot length, can be well approximated by a multivariate normal distribution. If there are p segmentation variables used, then there will be p mean values, and each segment will have a segment-specific mean vector μh of length p. In addition to the variances of the p segmentation variables, the covariance structure can also be modeled. This results in a $p \times p$ covariance matrix Σh for each segment. The covariance matrix Σh contains the variances of the p segmentation variables on the diagonal and the covariances between pairs of segmentation variables in the other entries. The covariance matrix is symmetric and contains $p(p + 1)/2$ unique values. The segment-specific parameters θh are a combination of the mean vector μh and the covariance matrix Σh. The number of parameters to estimate is $p + p(p + 1)/2$ accounting for the mean vector and the unique values in the covariance matrix.

Binary Distributions: The finite mixtures of binary distributions to model market segmentation based on binary segmentation variables representing customer activities. In this approach, binary segmentation variables are used to represent customer preferences or activities, where a value of 1 indicates engagement in a specific activity and 0 indicates non-engagement. The parameters of the segment-specific models, which represent the probabilities of observing a 1 in each variable, are extracted. These probabilities characterize the segments and can be used to create segment profiles. Overall, the mixture of binary distributions provides a way to model the association between binary variables and identify distinct market segments based on activity patterns.

Finite Mixtures of Regressions: Finite mixtures of regressions provide a different perspective on market segmentation compared to distance-based clustering methods. They analyze the relationship between variables and allow for the identification of distinct segments with varying regression patterns. 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:
The section highlights the importance of variable selection in segmentation analysis. While many segmentation algorithms assume that all variables contribute to determining the

segmentation olution, this may not always be the case. In situations where the segmentation variables contain redundant or noisy information, it becomes necessary to identify and select suitable variables for the analysis. variable selection plays a crucial role in segmentation analysis, especially when dealing with redundant or noisy variables. Different algorithms, such as biclustering, VSBD, and factor-cluster analysis, offer integrated approaches to segment extraction while simultaneously selecting suitable segmentation variables, taking into account the specific characteristics of binary data.

Biclustering Algorithms: Biclustering is a method for simultaneously clustering consumers and variables in market segmentation analysis. Biclustering algorithms can be applied to different types of data, including binary data. In the binary case, biclustering aims to extract market segments consisting of consumers who have a value of 1 for a specific group of variables. Biclustering offers advantages in market segmentation with a large number of variables. It avoids data transformation, which can introduce bias, and allows for the identification of niche markets by setting specific control parameters. However, biclustering methods may not group all consumers, leaving some ungrouped individuals who do not fit into any segment. Biclustering is a powerful approach for market segmentation analysis, particularly with binary data and a large number of variables. It enables the identification of groups of consumers and variables with common patterns, providing insights into niche markets and avoiding data transformation biases.

Variable Selection Procedure for Clustering Binary Data (VSBD): The VSBD method by Brusco is a variable selection procedure for clustering binary data. It uses the k-means algorithm and within-cluster sum-of-squares criterion to identify relevant variables and remove masking variables. The procedure involves an iterative process of adding variables based on their impact on the clustering solution, and it requires specifying the number of segments in advance.

4.3.3 Variable Reduction: Factor-Cluster Analysis: The factor-cluster analysis is a two-step procedure used for data-driven market segmentation analysis. In the first step, the segmentation variables are subjected to factor analysis, and the raw data is discarded. In the second step, market segments are extracted using the factor scores obtained from the factor analysis. Factor-cluster analysis is often used when the number of segmentation variables is too high relative to the sample size. factor-cluster analysis lacks conceptual justification and can result in a loss of information, data transformation, and difficulties in interpretation. It is generally recommended to perform cluster analysis on raw data rather than relying on factor scores for market segmentation purposes.

Data Structure Analysis: Data structure analysis in market segmentation is aimed at assessing the reliability and stability of segmentation solutions, rather than determining an optimal solution with a clear criterion. Since it is not feasible to validate multiple segmentation strategies simultaneously, validation in market segmentation typically focuses on evaluating the stability of solutions across repeated calculations. The purpose of data structure analysis is to gain insights into the properties of the data and guide methodological decisions. It helps determine whether natural, distinct, and well-separated market segments exist in the data. If such segments exist, they can be easily identified. If not, analysts need to explore various alternative solutions to identify the most useful segment(s) for the organization. There are four main approaches to data structure analysis:

Cluster indices: Cluster indices provide measures of within-cluster homogeneity and between-cluster separation. These indices help assess the quality of segmentation solutions and identify the number of segments that best fit the data.

Gorge plots: Gorge plots visually represent the stability of solutions by plotting the average within-cluster dissimilarity as the number of segments increases. Gorge plots can reveal the presence of well-separated segments and help determine the appropriate number of segments.

Global stability analysis: Global stability analysis examines the overall stability of segmentation solutions across multiple runs with slightly modified data or algorithms. It provides insights into the robustness of the identified segments and helps assess the reliability of the results.

Segment level stability analysis: Segment level stability analysis focuses on the stability of individual segments across different runs. It examines the consistency of segment membership and characteristics, allowing for a more detailed understanding of the stability and reliability of the segmentation solution. These approaches collectively contribute to data structure analysis and assist in making informed decisions about the number of segments to extract and the reliability of the segmentation results. By assessing the stability and structure of the data, analysts can gain valuable insights and choose the most appropriate segmentation solution for their organization

Step 6: Profiling Segments

6.1 Identifying Key Characteristics Segments

Profiling is essential in data-driven market segmentation to understand the characteristics and defining features of resulting market segments. Profiling is not required in commonsense segmentation, as the segments are predefined based on obvious characteristics like age groups. The aim of profiling in data-driven segmentation is to identify the defining characteristics of market segments based on the segmentation variables. Profiling involves characterizing the market segments individually and comparing them to other segments to understand their uniqueness. Data-driven market segmentation solutions can be challenging to interpret, and many managers struggle to understand the results, per the study by Dolnicar and Lazarevski (2009). Clear and concise presentation of segmentation results is crucial for effective decision-making.

6.2 Traditional Approaches To Profiling Market Segments

- Data-driven segmentation solutions are often presented in ways that can be challenging to interpret, such as high-level summaries that oversimplify segment characteristics or large tables with exact percentages for each segmentation variable.
- It illustrates the difficulty in interpreting segment characteristics based on exact percentages for each variable, requiring numerous comparisons between segments and the overall values. Profiling all segments in this manner can be a tedious and time-consuming task.
- Comparing multiple segmentation solutions further increases the complexity, as each solution may contain different segment definitions. In such cases, the number of comparisons needed to understand the defining characteristics of the segments becomes significantly higher, making it a challenging task for users.

6.3 Segment Profiling With Visualizations

- Graphics and data visualization play a crucial role in exploratory statistical analysis, including cluster analysis. They provide insights into the complex relationships between variables and make the interpretation of market segmentation results easier.
- Visualizations of segmentation solutions are valuable for inspecting segments in detail, interpreting segment profiles, and assessing the usefulness of different market segmentation solutions. They assist data analysts and users in making critical decisions when selecting the most appropriate segmentation solution.

6.4 Identifying Defining Characteristics Of Market Segment

- Segment profile plots provide a visual representation of how each market segment differs from the overall sample across segmentation variables. They are a direct translation of tables and allow for a quick understanding of the defining characteristics of each segment. Visualizations, such as segment profile plots, are easier and faster to interpret than tables, even when well-structured. They provide a comprehensive overview of segment differences and make the interpretation of segmentation results more accessible.
- The order of segmentation variables in visualizations can be rearranged to improve clarity and facilitate interpretation. Variables can be ordered based on similarity of answer patterns, such as through hierarchical clustering of the variables.
- Marker variables in segment profile plots are highlighted in color to indicate their significance in characterizing a segment. These variables have substantial differences in means compared to the overall sample, usually defined as deviating by more than 0.25 or 50% from the total mean.
- Visualizations, like segment profile plots, help in assessing the usefulness of a market segmentation solution and support the decision-making process of selecting the most appropriate solution. They enable data analysts and users to compare and evaluate different segment profiles.

- Eye tracking studies have shown that visualizations, such as segment profile plots, require less cognitive effort and processing time compared to tables. They allow for faster extraction of information, leading to easier interpretation and comprehension of segmentation results. Well-designed graphs offer a valuable return on investment, especially for managers making strategic decisions based on segmentation outcomes.

6.5 Assessing Segment Separation:

- Segment separation plots visualize the overlap of segments in the data space, providing an overview of the separation between segments. They are particularly useful when the number of segmentation variables is low but can become complex as the number of variables increases.
- In segment separation plots, scatter plots display the original data points colored by segment membership, while cluster hulls indicate the shape and spread of the true segments. Neighbourhood graphs show similarity between segments, with thicker lines indicating more observations sharing segment centers.
- For higher-dimensional data sets, projection techniques like principal component analysis can be used to reduce the dimensions and create segment separation plots. This allows for a visual representation of segment separation in a reduced-dimensional space.
- Segment separation plots can become cluttered and hard to interpret due to overlapping segments, especially when there is limited separation between segments. Adjustments can be made, such as modifying colors, omitting observations, and highlighting the inner areas of each segment, to improve readability and interpretation.
- Segment separation plots visualize a specific projection of the data, and different projections may result in different separation patterns. It is important to consider multiple projections and not draw conclusions solely based on a single visualization. Interpretation should be based on the specific projection shown and the characteristics of the data.

Step 7: Describing Segments

In step 7, describes the segments using additional information like the Consumer's age, gender, past travel behavior, preferred vacation activities, media use, etc. These additional variables are called descriptive variables.

Using Visualisations to Describe Market Segments:

- Nominal and Ordinal Descriptor Variables:
  The Nominal and Ordinal Descriptor Variables include features like gender, level of education, country of origin, etc. To visualize these variables, we first need to encode Them as a categorical variable with some numeric form and then do the plotting.

These plots can be charts of different kinds to enhance visualization. Examples include
bar charts and mosaic chart. Mosaic plots can also be encoded with color combinations for better representation.

- Metric Descriptor Variables : The variables are of continuous numeric data type. Examples include age, number of nights at the tourist destinations,and money spent on accommodation. The best representation of these variables is done by histograms. Other forms of graphs can also be used to visualize data, like box-and-whisker plot.
- Predicting Segments from Descriptor Variables : We can use regression models to predict segments from the data. Regression analysis is the basis of prediction models. Regression analysis assumes that a dependent variable y can be predicted using independent variables or regressors.
- Linear Regression: The most basic form of regression model is the linear regression model. It assumes that function is linear and that y follows a normal distribution with a mean and a variance. In linear regression models, regression coefficients express how much the dependent variable changes if one independent variable changes while all other independent variables remainconstant.
- Binary Logistic Regression : a regression model for binary data using generalised linear models by assuming that $f(y|\mu)$ is the Bernoulli distribution with success probability μ, and by choosingthe logit link that maps the success probability $\mu \in (0, 1)$ onto $(-\infty,\infty)$ by $g(\mu) = \eta = \log(\mu / 1 - \mu)$ In binomial logistic regression, the intercept gives the value of the linear predictor η if the independent variables $x1,\ldots,xp$ all have a value of 0.
- Multinomial Logistic Regression : Multinomial logistic regression can fit a model that predicts each segment simultaneously. Because segment extraction typically results in more than two market segments, the dependent variable y is not binary. Rather, it is categorical and assumed to follow a multinomial distribution with the logistic function as link function.
- Tree-Based Methods : Classification and regression trees are a supervised learning technique from machine learning. The advantages of classification and regression trees are their ability to performvariable selection, ease of interpretation supported by visualisations, and the straight- forward incorporation of interaction effects.

Step 8: Selecting the Target Segment(s)

Market Segment Evaluation In target market selection, decision matrices are commonly used to visualize the relative segment attractiveness and relative organizational competitiveness for each market segment. Various names, such as the Boston matrix, General Electric/McKinsey matrix, directional policy matrix, and market attractiveness-business strength matrix, are used for these matrices. The purpose of these matrices is to facilitate the evaluation of alternative market segments and aid in the selection of one or a few segments for targeting.

The decision matrix plots two criteria along the axes: segment attractiveness and relative organizational competitiveness specific to each segment. Segment attractiveness represents how desirable the segment is for the organization, while relative organizational competitiveness assesses the likelihood of the organization being chosen by the segment. To simplify the evaluation, the axes can be labeled as "How attractive is the segment to us?" and "How attractive are we to the segment?"   In the example provided, a generic segment evaluation plot is used, where segments are represented as circles. The size of the circles can reflect additional criteria such as contribution to turnover or loyalty. The assessment of segment attractiveness and relative organizational competitiveness depends on the organization's specifications and criteria established in Step 2 of the market segmentation analysis. The criteria of segment attractiveness and their respective weights are determined, quantifying their impact on the overall value of segment attractiveness.   To select a target segment in Step 8, the segmentation team needs to assign values for each attractiveness criterion to each segment.

These values emerge from the grouping, profiling, and description of each market segment conducted in Steps 6 and 7. The location of each market segment in the segment evaluation plot is calculated by multiplying the weight of each attractiveness criterion with its assigned value for each segment. These weighted values are then summed to represent a segment's overall attractiveness, which is plotted along the x-axis of the decision matrix.   The same procedure is followed for evaluating relative organizational competitiveness. The criteria used by consumers to choose between alternative offers in the market are considered, such as product attractiveness, price suitability, distribution channel availability, and segment awareness of the organization or brand image.   By utilizing the decision matrix and assigning values to the criteria for each segment, the segmentation team can assess and compare the segment attractiveness and relative organizational competitiveness, ultimately aiding in the selection of the target segment(s) for the organization's marketing efforts.

Step 9: Customising the Marketing Mix

Implications for Marketing Mix Decisions
Rather, it goes hand in hand with the other areas of strategic marketing, most importantly: positioning and competition. In fact, the segmentation process is frequently seen as part of what is referred to as the segmentation-targeting-positioning (STP) approach. The segmentation-targeting-positioning approach postulates a sequential process. The process starts with market segmentation (the extraction, profiling, and description of segments), followed by targeting (the assessment of segments and selection of a target segment), and finally positioning (the measures an organisation can take to ensure that their product is perceived as distinctly different from competing products, and in line with segment needs).

Viewing market segmentation as the first step in the segmentation-targeting positioning approach is useful because it ensures that segmentation is not seen as independent from other strategic decisions. It is important, however, not to adhere too strictly to the sequential nature of the segmentation-targeting-positioning process. It may well be necessary to move back and forward from the segmentation to the targeting step, before being in the position of making a long-term commitment to one or a small number of target segments.

Fig: How the target segment decision affects marketing mix development

Figure illustrates how the target segment decision – which has to be integrated with other strategic areas such as competition and positioning – affects the development of the marketing mix. For reasons of simplicity, the traditional 4Ps model of the marketing mix including Product, Price, Place, and Promotion serves as the basis of this discussion.

Product: One of the key decisions an organisation needs to make when developing the product dimension of the marketing mix, is to specify the product in view of customer needs. Often this does not imply designing an entirely new product, but rather modifying an existing one. Other 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.

Price: Typical decisions an organisation needs to make when developing the price dimension of the marketing mix include setting the price for a product, and deciding on discounts to be offered.

Place: The key decision relating to 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.

Promotion: Typical 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. Other tools in the promotion category of the marketing mix include public relations, personal selling, and sponsorship.

Step 10: Evaluation and Monitoring

After the market segmentation analysis is completed, and all strategic and tactical marketing activities have been undertaken, the success of the market segmentation strategy has to be evaluated, and the market must be carefully monitored on a continuous basis.

Case Study: Fast Food- McDonald

McDonald's is one of the most popular restaurant chains in the world. Nowadays, there are more than 40000 McDonald's restaurants globally which serve tens of millions of customers every day. The question becomes what did McDonald's do in order to make sure its customers stuck on McDonald's products? The difficult part is that each of the customers has a different profile. The profile could include elements as broad as nationality and elements that are much more specific such as preference of meat. To satisfy all these needs, it's crucial to know about customers and build a marketing segmentation so that the other departments can start advertising and branding accordingly. Indeed, McDonald's marketing team does a lot of work and one of its jobs is to build customer segmentation in order to know their customers better and target new potential customers. In the following text, the goal is to explore what approaches McDonald's use to build marketing segmentation.

The data set contains responses from 1453 adult Australian consumers relating to their perceptions of McDonald's with respect to the following attributes: YUMMY, CONVENIENT, SPICY, FATTENING, GREASY, FAST, CHEAP, TASTY, EXPENSIVE, HEALTHY, and DISGUSTING. These attributes emerged from a qualitative study conducted in preparation of the survey study. For each of those attributes, respondents provided either a YES response (indicating that they feel McDonald's possesses this attribute), or a NO response (indicating that McDonald's does not possess this attribute).
In addition, respondents indicated their AGE and GENDER. Had this data been collected for a real market segmentation study, additional information – such as details about their dining out behavior, and their use of information channels – would have been collected to enable the development of a richer and more detailed description of each market segment.

GitHub Link:
https://github.com/DivyaGazinkar/Machine-Learning-Internship-2023/tree/main/Market%20Segmentation%20and%20Case%20Study/McDonalds%20Case%20Study