SUMMARY OF MARKET SEGMENTATION ANALYSIS

Introduction

Market segmentation is the process of dividing a larger market into smaller, distinct groups of consumers who share similar characteristics, needs, or behaviours. The goal is to identify specific segments within the target market and develop tailored marketing strategies and messages for each segment. A marketing plan consists of both strategic and tactical components.

The strategic marketing plan provides a comprehensive document outlining the goals, objectives, strategies, and tactics for the company's marketing activities. It serves as a roadmap for the marketing team, guiding their actions to achieve specific business outcomes. For example, expanding into new markets and increasing market share may be a strategic objective. Strategies to accomplish this could include market research, adapting products/services, localized marketing approaches, collaboration with local partners, targeted advertising, and monitoring performance.

Step-1: Deciding (not) to Segment

1. Implications of committing to Market Segmentation

Successful implementation of a market segmentation strategy requires a significant and ongoing commitment in the long term. This entails making substantial changes and investments in various aspects of the business. An organization needs to incur costs for conducting research, surveys, and designing strategies tailored to specific market segments. There is a need for organizational adjustments to prioritize and cater to the identified market segments. Effective decision-making by executives plays a critical role in the success of a market segmentation strategy.

2. Implementation Barriers

The absence of a market or consumer-centric approach, coupled with resistance to change, can impede successful segmentation efforts. Inadequate leadership support and resource allocation can hinder effective segmentation analysis and implementation.
Ineffective communication, limited information sharing, and short-term thinking hinder the ability to adopt creative ideas and make necessary changes in segmentation strategies. Resistance to unfamiliar management techniques can be overcome by providing easily comprehensible market segmentation analysis and presenting results in a clear manner.

Step-2: Specifying the Ideal Target Segment

1. **Segment Evaluation Criteria**
   Analyse the unique needs, preferences, and pain points of each segment. Prioritize segments that closely align with your business's products, capabilities, and value propositions. Prioritize segments that demonstrate growth potential in terms of customer base, market value, or industry trends, considering their size and future growth prospects. Assess the profitability of each segment by evaluating factors such as purchasing power, willingness to pay, and potential profit margins. Focus on segments that offer attractive revenue opportunities. Evaluate the competitive landscape within each segment, considering the number and strength of competitors targeting the same segment. Assess your ability to differentiate and gain a competitive advantage.

2. **Knock-Out Criteria**
   The segment must be of sufficient size to justify the allocation of resources for customized marketing efforts, ensuring that there are enough consumers within the segment to make it worthwhile. The segment should be distinct, meaning consumers in the segment should have discernible differences from individuals in other segments in terms of their required characteristics or behaviours. The segment must exhibit homogeneity, with consumers sharing similar characteristics or behaviours within the segment, enabling targeted marketing strategies.

3. **Attractiveness Criteria**
   The segmentation team can consider evaluating the desirability of different market segments. Market segments are not simply classified as meeting or not meeting attractiveness criteria; instead, each segment is assessed and rated based on its level of attractiveness across various criteria. The overall attractiveness, considering all criteria, plays a crucial role in selecting target segments during the market segmentation analysis.

4. **Implementing a Structured Process**
   Develop detailed profiles for the top-ranked segments and tailor your marketing strategies to effectively target and serve those segments. Establish clear evaluation criteria based on your business goals to assess the attractiveness of different segments. Conduct comprehensive market research and gather relevant data to inform segmentation decisions. Analyse and prioritize potential segments based on the established criteria to identify the most promising opportunities.

In Step 2 of the process, the segmentation team aims to create a list of around six criteria that determine the attractiveness of each segment. These criteria are assigned weights to indicate their relative importance. The team determines the weights through discussions and negotiations. It is beneficial to seek approval from the advisory committee, which consists of representatives from different organizational units, as it allows for considering multiple perspectives. In summary, Step 2 involves defining knock-out criteria, selecting a subset of attractiveness criteria, assigning weights to each criterion, and obtaining approval from the advisory committee.

Step 3: Collecting Data

3.1 Segmentation Variable

Describing segments in detail using empirical data is crucial for developing an effective marketing mix and targeting strategies tailored to specific segments, including socio-demographics and media behavior. In commonsense segmentation, a single characteristic is used as the segmentation variable to split the sample into segments, while other personal characteristics serve as descriptor variables to provide detailed segment descriptions. Data-driven market segmentation requires high-quality empirical data to ensure the accuracy and effectiveness of the extracted market segments and their descriptions, enabling customized product development, pricing strategies, distribution channel selection, and advertising campaigns.

3.2 Segmentation Criteria

The choice of segmentation criterion is a critical decision that organizations need to make before conducting market segmentation, as it determines the nature of the information used for segmentation. The decision of which segmentation criterion to use requires prior market knowledge and cannot be easily delegated to consultants or data analysts. Common segmentation criteria include geographic, socio-demographic, psychographic, and behavioural factors.

3.3 Data from Survey Studies

Survey data is commonly used for market segmentation analysis due to its affordability and ease of collection, making it a feasible approach for organizations. Survey data can be prone to biases that can impact the quality of market segmentation solutions. It is important to consider and address these biases to ensure the accuracy and reliability of the analysis.

3.4 Data from Internal Sources

Internal data provides valuable insights into actual consumer behaviour. Internal data is automatically generated and easily accessible, requiring no additional data collection effort. Using internal data for market segmentation analysis may result in biased representations of consumer preferences, as it may over-represent existing customers and overlook potential future customers.

3.5 Data from Experimental Studies

Experimental data, whether from field or laboratory experiments, can provide valuable insights into consumer responses to advertisements or product attributes. The results of experiments can be used as segmentation criteria, such as measuring consumer preferences based on their response to stimuli. Conjoint studies and choice experiments reveal how product attributes impact consumer choice, serving as useful segmentation criteria.

Step 4: Exploring Data

4.1 First Glimpse at the Data Set

The Australian travel motive data set contains 32 columns and 1000 rows. The variable Age of respondents is a metric variable summarised by the minimum value, the first quartile, the median, the mean, the third quartile and the maximum. The variables Income and Income2 have 66 missing values. The variable Income2 reveals that the categories are not sorted in order.

4.2 Data Cleaning

Identify and address missing values in the data set with the techniques such as imputation or removal of records or variables with a high proportion of missing values. Detect and handle outliers which can be removed, transformed, or treated separately based on the nature of the data and the analysis goals. Ensure consistent data formats across variables to eliminate inconsistencies that may affect data analysis and interpretation. Address categorical variables by using a helper variable and the factor() and level() functions to ensure proper representation and control over the ordering. Maintain a record of the data cleaning steps performed. This documentation helps ensure transparency, reproducibility, and provides an audit trail for future reference or collaboration. No data cleaning is necessary for the Gender and Age variables as they are already in a suitable and clean format.

4.3 Descriptive Analysis

Numeric and visual representations of data provide valuable insights, allowing for descriptive analysis and statistical software packages provide an extensive range of tools to facilitate descriptive analysis. Histograms visually depict the frequency and distribution of numeric variables, revealing if the distribution is unimodal, symmetric, or skewed. Histograms, boxplots, and scatter plots are useful graphical methods for analysing numeric data. Bar plots are effective for visualizing the frequency counts of categorical variables. Mosaic plots provide a visual representation of the association between multiple categorical variables. In the Australian travel motives data set, the boxplot reveals that the distribution of age is right-skewed. This is indicated by the median being positioned more towards the left, rather than in the middle of the box. The graphical examination of the data reinforces that the variables in the Australian travel motives data set are appropriate for segmentation purposes.

4.4 Pre-Processing

The commonly used pre-processing procedures for categorical variables are merging levels of categorical variables and converting them into numeric representations. Merging levels of categorical variables is useful if the original categories are too differentiated. Categorical data can be converted to numeric data if it is ordinal, where the categories have a natural order or ranking. To balance the influence of segmentation variables on segmentation results, variables can be standardised.

4.5 Principal Components Analysis

PCA is a data transformation technique that converts a multivariate dataset into uncorrelated principal components, ordered by their importance in explaining the data's variability. The variability in the data is primarily captured by the first principal component, followed by the second principal component, and so forth, in descending order of importance. The transformation derived from PCA is utilized to reduce the dimensionality of high-dimensional data, enabling visualization by projecting it into lower dimensions. For variables with similar scales and ranges, the covariance matrix is suitable, while the correlation matrix should be used for variables with different scales or dissimilar ranges. Variables that exhibit strong correlation will exhibit high loadings on the same principal components, suggesting redundancy in the captured information. Scatter plot matrix can be used to visualize principal components.

4.6 PCA Outcome

The first principal component accounts for approximately 18% of the variance in the original data, while the second principal component explains around 9% of the variance. Principal components 3 to 15 account for a range of only 8% to 3% of the original variation. The relatively low variance explained by the initial principal components suggests the necessity of retaining all the original variables for effective segmentation. In this case, PCA does not provide substantial assistance in visualizing the data in a lower dimensional space.

Step 5: Extracting Segments

5.1 Grouping Consumers

Data-driven market segmentation analysis is inherently exploratory due to the nature of consumer data sets, which are often unstructured. Consumer preferences vary widely, making it difficult to identify clear groups based on product preferences alone. As a result, segmentation methods heavily rely on assumptions about the structure of consumer segments. Consequently, the outcome of a market segmentation analysis is influenced by both the underlying data and the chosen extraction algorithm. The segmentation methods employed play a crucial role in shaping the resulting segmentation solution.

5.2 Distance-based methods

Distance-based methods use a particular notion of similarity or distance between observations (consumers), and try to find groups of similar observations (market segments). Numerous approaches to measuring the distance between two vectors exist; several are used routinely in cluster analysis and market segmentation. A distance is a function $d(\cdot, \cdot)$ with two arguments: the two vectors x and y between which the distance is being calculated. The result is the distance between them (a nonnegative value).

A distance measure has to comply with a few criteria.
One criterion is symmetry, that is:
$d(x, y) = d(y, x)$.
A second criterion is that the distance of a vector to itself and only to itself is 0:
$d(x, y) = 0 \Leftrightarrow x = y$
In addition, most distance measures fulfill the so-called triangle inequality:
$d(x, z) \leq d(x, y) + d(y, z)$

Hierarchical Methods

Hierarchical clustering methods are the most intuitive way of grouping data because they mimic how a human would approach the task of dividing a set of n observations (consumers) into k groups (segments). If the aim is to have one large market segment ($k = 1$), the only possible solution is one big market segment containing all consumers in data X. At the other extreme, if the aim is to have as many market segments as there are consumers in the data set ($k = n$), the number of market segments has to be n, with each segment containing exactly one consumer. Each consumer represents their own cluster. Market segmentation analysis occurs between those two extremes.

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.
Agglomerative hierarchical clustering approaches the task from the other end. The starting point is each consumer representing their own market segment (n singleton

clusters). Step-by-step, the two market segments closest to one another are merged until the complete data set forms one large market segment.

Partitioning Methods

Hierarchical clustering methods are well suited for analyzing small data sets with up to a few hundred observations. However, for larger data sets, dendrograms become difficult to interpret, and the pairwise distance matrix may not fit into computer memory. In such cases, clustering methods that create a single partition are more suitable than hierarchical approaches. These methods calculate distances only between each consumer in the data set and the center of the segments, rather than computing all pairwise distances at the beginning of the analysis. For instance, in a data set with 1000 consumers, an agglomerative hierarchical clustering algorithm would need to compute (1000×999)/2 = 499,500 distances for the pairwise distance matrix. In contrast, a partitioning clustering algorithm aiming to extract five market segments would only need to calculate between 5 and 5000 distances at each step of the process, depending on the specific algorithm used. Additionally, when extracting only a few segments, it is more effective to optimize the algorithm directly for that goal rather than constructing the complete dendrogram and then making heuristic cuts to form segments.

K- means and k-centroid clustering

It is an iterative algorithm that divides the unlabeled dataset into k different clusters in such a way that each dataset belongs to only one group that has similar properties. It allows us to cluster the data into different groups and a convenient way to discover the categories of groups in the unlabeled dataset on its own without the need for any training. It is a centroid-based algorithm, where each cluster is associated with a centroid. The main aim of this algorithm is to minimize the sum of distances between the data point and their corresponding clusters. The algorithm takes the unlabeled dataset as input, divides the dataset into k-number of clusters, and repeats the process until it does not find the best clusters. The value of k should be predetermined in this algorithm. The k-means clustering algorithm mainly performs two tasks: ● Determines the best value for K center points or centroids by an iterative process. ● Assigns each data point to its closest k-center. Those data points which are near to the particular k-center, create a cluster. Hence each cluster has data points with some commonalities, and it is away from other clusters.

Improved k-means

Various attempts have been made to enhance the k-means clustering algorithm, and one straightforward improvement is to use intelligent initialization methods instead of randomly selecting k consumers as starting points. Randomly selecting consumers as initial points can be suboptimal because some of them may be located close to each other and not accurately represent the entire data space. This increases the risk of the k-means algorithm becoming trapped in a local optimum, which is a good solution but not necessarily the best one. To overcome this issue, one approach is to initialize the algorithm with starting points that are evenly distributed across the entire data space. Such initialization helps in capturing the overall representation of the entire data set, thus minimizing the chances of being stuck in a local optimum.

Hard Competitive Learning

Hard competitive learning, also known as learning vector quantization, is a variation of the standard k-means algorithm for segment extraction. While both methods aim to minimize the sum of distances between consumers and their closest representative (centroid), the process of achieving this goal differs slightly. In k-means, all consumers in the data set are used in each iteration to determine new segment representatives (centroids). In hard competitive learning, on the other hand, a single consumer is randomly selected, and the closest segment representative to that consumer is moved slightly towards the selected consumer. This procedural difference can lead to different segmentation solutions, even when the same starting points are used. Furthermore, hard competitive learning may find the globally optimal market segmentation solution, while k-means can get trapped in a local optimum, or vice versa. Neither method is inherently superior to the other; they are simply different approaches with their own characteristics.

Hybrid approaches

Hybrid segmentation approaches aim to address these issues by first running a partitioning algorithm on the data, extracting a larger number of segments than desired. Then, only the segment centers (centroids) and sizes are retained, discarding the original data. These reduced representations are then used as input for hierarchical clustering, benefiting from the lower memory requirements. The resulting dendrogram can help determine the appropriate number of segments to extract, considering the inter-segment distances and relationships. By combining the strengths of both approaches, hybrid methods offer a way to handle large data sets while still obtaining meaningful and interpretable market segmentation solutions.

Two-Step Clustering

Two-step clustering, also known as two-stage clustering, is a technique commonly used in market segmentation analysis. It involves a two-step process to identify distinct consumer segments. In the first step, the data is preprocessed to reduce dimensionality and handle outliers. This step is crucial for improving the efficiency and effectiveness of the clustering process. Techniques such as principal component analysis (PCA) or feature selection methods may be used. Once the data is prepared, the second step involves performing the actual clustering. In this step, a two-step clustering algorithm is applied. This algorithm combines elements of hierarchical clustering and partitioning clustering. The algorithm begins by using a hierarchical clustering approach to create an initial set of small subgroups or "preclusters." These preclusters are formed by iteratively merging similar data points based on a distance or similarity measure. In the second stage, a partitioning clustering algorithm, such as k-means or k-medoids, is applied to the preclusters obtained from the first stage. This algorithm further refines the segmentation by assigning each precluster to a final cluster based on within-cluster similarities. The advantage of the two-step clustering approach is that it combines the strengths of both hierarchical and partitioning methods. It is able to handle large data sets and can efficiently identify meaningful segments. Additionally, it does not require specifying the number of clusters in advance, as the algorithm determines the appropriate number based on the data. Two-step clustering has been widely used in market segmentation analysis as it provides a robust and flexible approach to segmenting consumer data, taking into account both local and global characteristics of the data.

Bagged Clustering

It involves creating multiple subsets of the original data through bootstrap sampling and performing clustering independently on each subset. The clustering results from these subsets are then aggregated to form a final segmentation solution. Bagged clustering enhances the stability, robustness, and generalization of the segmentation analysis by reducing the impact of outliers and random variations in the data. It also provides a more comprehensive representation of the underlying patterns in the market segments, resulting in more reliable and flexible segmentation outcomes.

5.3 Model Based Methods

Finite Mixtures of Distributions

The simplest case of model-based clustering has no independent variables x, and simply fits a distribution to y. To compare this with distance-based methods, finite mixtures of distributions basically use the same segmentation variables: a number of pieces of information about consumers, such as the activities they engage in when on vacation. No additional information about these consumers, such as total travel expenditures, is simultaneously included in the model.

Normal Distributions

For metric data, the most popular finite mixture model is a mixture of several multivariate normal distributions. The multivariate normal distribution can easily model covariance between variables; and approximate multivariate normal distributions occur in both biology and business. Mathematically, the multivariate normal distribution has two sets of parameters (mean and variance) like the univariate normal distribution. If p segmentation variables are used, these have p mean values, and each segment has a segment-specific mean vector μh of length p. In addition to the p variances of the p segmentation variables, the covariance structure can be modelled, resulting in a p ×p covariance matrix h for each segment. The covariance matrix h contains the variances of the p segmentation variables in 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 the combination of the mean vector μh and the covariance matrix h, and the number of parameters to estimate is p + p(p + 1)/2.

Binary Distributions

For binary data, finite mixtures of binary distributions, sometimes also referred to as latent class models or latent class analysis are popular. 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). The mixture model assumes that respondents in different segments have different probabilities of undertaking certain activities. These models, such as logistic regression or probit models, estimate the probability of consumers making a specific binary choice based on various independent variables. By fitting these models to the data, marketers can segment consumers based on their preferences, behaviours, or purchase decisions. This approach provides interpretable results, allowing marketers to understand the factors influencing consumer choices and develop targeted marketing strategies tailored to each segment. Binary distributions offer a probabilistic framework to uncover insights and drive effective market segmentation.

Finite Mixtures of Regressions

Finite mixtures of distributions are similar to distance-based clustering methods and – in many cases – result in similar solutions. Compared to hierarchical or partitioning clustering methods, mixture models sometimes produce more useful, and sometimes less useful solutions. Finite mixtures of regression models offer a completely different type of market segmentation analysis. 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.

5.4 Algorithms with Integrated Variable Selection

Most algorithms focus only on extracting segments from data. These algorithms assume that each of the segmentation variables makes a contribution to determining the segmentation solution. But this is not always the case. Sometimes, segmentation variables were not carefully selected, and contain redundant or noisy variables. Preprocessing methods can identify them. When the segmentation variables are binary, and redundant or noisy variables can not be identified and removed during data pre-processing in Step 4, suitable segmentation variables need to be identified during segment extraction. A number of algorithms extract segments while simultaneously selecting suitable segmentation.

Biclustering Algorithms

Biclustering simultaneously clusters both consumers and variables. Biclustering algorithms exist for any kind of data, including metric and binary. This section focuses on the binary case where these algorithms aim at extracting market segments containing consumers who all have a value of 1 for a group of variables. These groups of consumers and variables together then form the bicluster. Biclustering offers several advantages in market segmentation. Unlike data transformation approaches, biclustering does not alter the original data, minimizing the risk of biased segmentation results. It identifies identical patterns displayed by groups of consumers with respect to groups of variables, making it effective in capturing niche markets. By adjusting the matching requirements, biclustering can generate smaller, highly homogeneous segments for niche markets or larger, less homogeneous segments for broader market segments. This flexibility allows marketers to uncover meaningful consumer subgroups without the need for extensive data transformation, enhancing the accuracy and relevance of the segmentation analysis.

Variable Selection Procedure for Clustering Binary Data (VSBD)

The procedure first identifies the best small subset of variables to extract segments. Because the procedure is based on the k-means algorithm, the performance criterion used to assess a specific subset of variables is the within-cluster sum-ofsquares (the sum of squared Euclidean distances between each observation and their segment representative). This is the criterion minimised by the k-means algorithm. After having identified this subset, the procedure adds additional variables one by one. The variable added is the one leading 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. The number of segments k has to be specified in advance.

Variable Reduction: Factor-Cluster Analysis

The term factor-cluster analysis refers to a two-step procedure of data-driven market segmentation analysis. In the first step, segmentation variables are factor analysed. The raw data, the original segmentation variables, are then discarded. In the second step, the factor scores resulting from the factor analysis are used to extract market segments.

5.5 Data Structure Analysis

Data structure analysis provides valuable insights into the properties of the data. These insights guide subsequent methodological decisions. Most importantly, stability-based data structure analysis provides an indication of whether natural, distinct, and well-separated market segments exist in the data or not. If they do, they can be revealed easily. 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 organisation.

Internal Cluster Indices

Internal cluster indices are metrics used in market segmentation to assess the quality and validity of clustering solutions. They provide quantitative measures of compactness and separation within the clusters, aiding in evaluating the effectiveness of the segmentation results. Compactness indices, such as intra-cluster distance or variance, evaluate how closely the data points within each cluster are grouped together. Separation indices, such as inter-cluster distance or centroid dissimilarity, measure the distinctiveness and separation between different clusters. By comparing these indices, marketers can select the most appropriate clustering solution that produces compact and well-separated clusters. Internal cluster indices also assist in determining the optimal number of clusters by evaluating the stability and coherence of the segmentation solutions. They enable comparisons between different clustering algorithms or varying the number of clusters, helping marketers make informed decisions about the segmentation approach. However, it is important to consider the limitations of internal cluster indices, as they solely rely on the data characteristics and do not incorporate external validation or domain-specific knowledge. To obtain a comprehensive evaluation, it is recommended to use multiple indices and consider the collective insights they provide when interpreting and selecting the segmentation solution.

External Cluster Indices

External cluster indices are metrics used in market segmentation to assess the agreement between the clustering results and external criteria or ground truth labels. These indices provide an objective evaluation of the segmentation quality by comparing the obtained clusters with known or pre-defined classifications. Common external cluster indices include the Rand Index, Jaccard Index, and Fowlkes-Mallows Index. Higher values indicate stronger agreement between the clustering solution and the external criteria, suggesting more accurate and valid segmentation results. External cluster indices are valuable for validating and benchmarking clustering algorithms, ensuring that the identified market segments align with established classifications or expert knowledge.

Global Stability Analysis

Global stability refers to the consistency and robustness of clustering solutions across multiple iterations or data samples. It assesses whether the identified market segments remain stable and consistent over time or across different subsets of the data. A segmentation solution is considered globally stable if it consistently produces similar clustering results, indicating that the identified segments reflect the underlying structure of the data rather than random variations. Evaluating global stability helps ensure the reliability and generalizability of the segmentation analysis, providing confidence that the identified market segments are not artifacts of specific data samples or random fluctuations. Techniques such as bootstrapping, resampling, or cross-validation can be used to assess the global stability of market segmentation results.

Segment Level Stability Analysis

When selecting a market segmentation solution, relying solely on global stability analysis may not guarantee the presence of a single best market segment. While global stability ensures overall consistency, it may overlook the stability of individual segments. It is important to assess both global stability and segment-level stability to avoid prematurely discarding solutions that may contain interesting and stable segments. Considering segment-level stability helps protect against disregarding valuable target segments. While organizations typically aim for a single target segment, evaluating the stability of individual segments alongside global stability ensures a more comprehensive assessment and selection of the optimal market segmentation solution.

Segment Level Stability Within Solutions (SLSW)

Segment level stability within solutions (SLSW) measures how often a market segment with the same characteristics is identified across several repeated calculations of segmentation solutions with the same number of segments. It is calculated by drawing several bootstrap samples, calculating segmentation solutions independently for each of those bootstrap samples, and then determining the maximum agreement across all repeated calculations.

Segment Level Stability Across Solutions (SLSA)

The purpose of this criterion is to determine the re-occurrence of a market segment across market segmentation solutions containing different numbers of segments. High values of segment level stability across solutions (SLSA) serve as indicators of market segments occurring naturally in the data, rather than being artificially created. Natural segments are more attractive to organisations because they exist, and no managerial judgement is needed in the artificial construction of segments.

Step 6: Profiling Segments

6.1 Identifying Key Characteristics of Market Segments

Profiling the segments is essential in order to understand the characteristics of each segment resulting from the data-driven segmentation process. Profiling involves identifying and describing the key attributes and defining characteristics of the market segments based on the segmentation variables.

While predefined or commonsense segmentation may not require this step, data-driven segmentation often necessitates profiling to uncover the distinguishing features of each segment. For example, if the segmentation is based on consumer benefits sought, the specific characteristics of the resulting segments may not be known until the data is analyzed.

Profiling involves characterizing each market segment individually and comparing them to one another. It helps differentiate a segment from others and provides insights for interpreting the segmentation results correctly. Good profiling is crucial for making strategic marketing decisions based on the segmented data.

Interpreting data-driven segmentation solutions can be challenging for managers. Research has shown that many marketing managers struggle to understand and interpret these solutions. They often find the results presented in lengthy reports without clear executive summaries or in a rushed and confusing manner. The information may be presented in numerical or percentage form across a few variables, but it may lack conclusiveness and meaning.

To facilitate profiling and minimize misinterpretation, graphical statistics approaches can be employed. These approaches use visual representations to present the profiling information, making it less tedious and easier to comprehend.

In traditional approaches to profiling market segments, the data analyst typically presents the segmentation results in the form of large tables. These tables provide the exact percentages of segment members that agree or engage in specific travel motives or attributes. However, such tables can be challenging to interpret and make it difficult to gain a quick overview of the key insights.

6.2 Traditional Approaches to Profiling Market Segments

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Visualizations help in interpreting and assessing the usefulness of market segmentation solutions. They assist data analysts and users in selecting the most appropriate solution from the numerous alternatives that arise during the segmentation process. By visualizing segment profiles, statistical graphs enable the identification of defining characteristics for each market segment and highlight how they differ from the overall sample.

6.3 Segment Profiling with Visualisations

Segment separation plots are visualizations that depict the overlap of segments in a data space. They provide a quick overview of the data situation and the segmentation solution. The plots can be simple when there are a low number of segmentation variables but become more complex as the number of variables increases.
In the segment separation plot, observations are represented as points in a scatter plot, with each observation colored according to its segment membership. The plot also includes cluster hulls, which indicate the shape and spread of the segments. The cluster hulls can be solid or dashed, representing different levels of inclusion of observations.
Neighborhood graphs are added to the plot to indicate the similarity between segments. These graphs consist of black lines connecting segment centers. A line is drawn between two segment centers if they are the two closest centers for at least one observation. The width of the line indicates the number of observations that have those two centers as their closest.

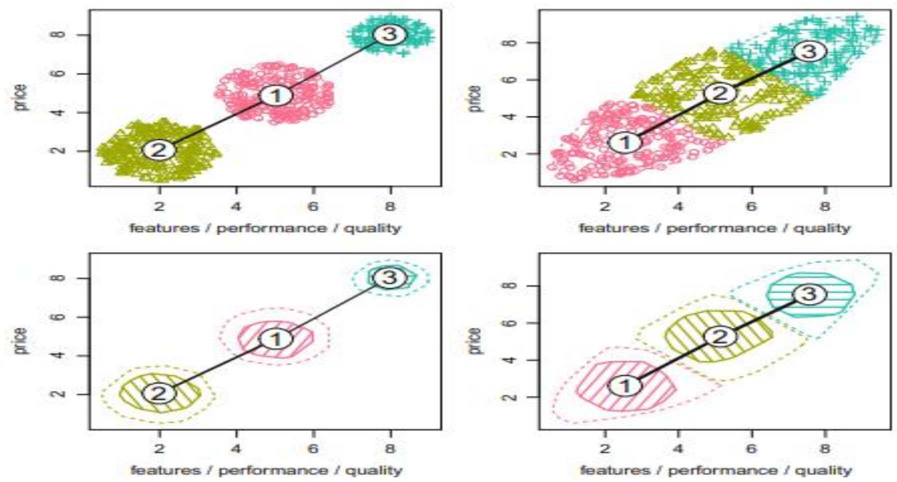

Fig. 8.4 Segment separation plot including observations (first row) and not including observations (second row) for two artificial data sets: three natural, well-separated clusters (left column); one elliptic cluster (right column)

In the provided example (Fig. 8.4), two artificial data sets are visualized using segment separation plots. The plots show scatter plots of the observations colored by segment membership, cluster hulls representing the segments' shape and spread, and neighborhood graphs indicating the similarity between segments.

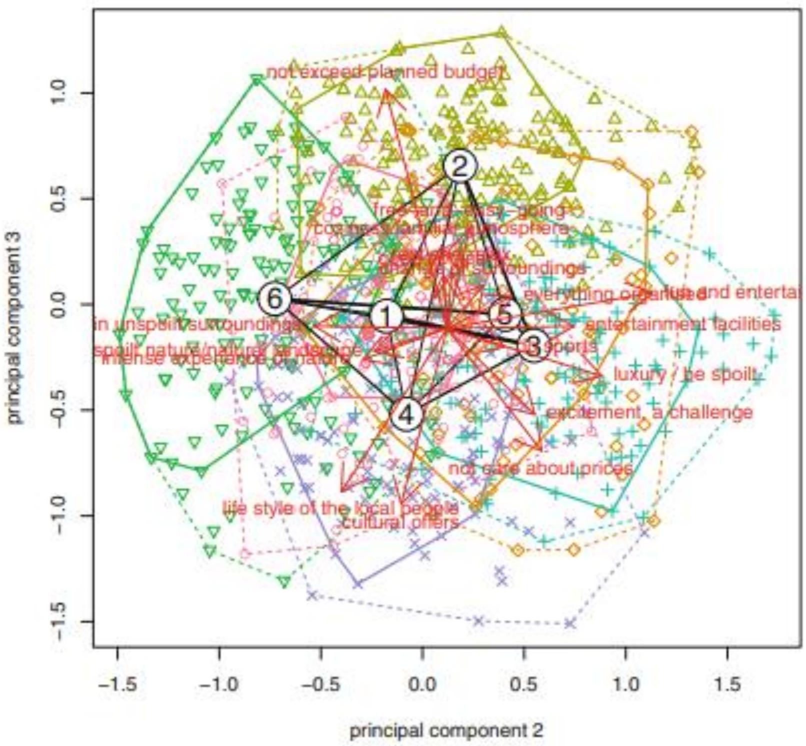

Fig. 8.5 Segment separation plot using principal components 2 and 3 for the Australian travel motives data set

For high-dimensional data, such as a 20-dimensional travel motives data set, a projection technique is used to reduce the dimensions and create a segment separation plot. Principal components analysis (PCA) is one such technique that can be applied to project the data onto a smaller number of dimensions. The resulting plot (Fig. 8.5) shows the segments in the reduced-dimensional space.

However, interpreting segment separation plots can be challenging, especially when there is overlap between segments. Different visual adjustments can be made to improve the readability of the plots, such as modifying colors, omitting observations, and highlighting only the inner area of each segment (Fig. 8.6).

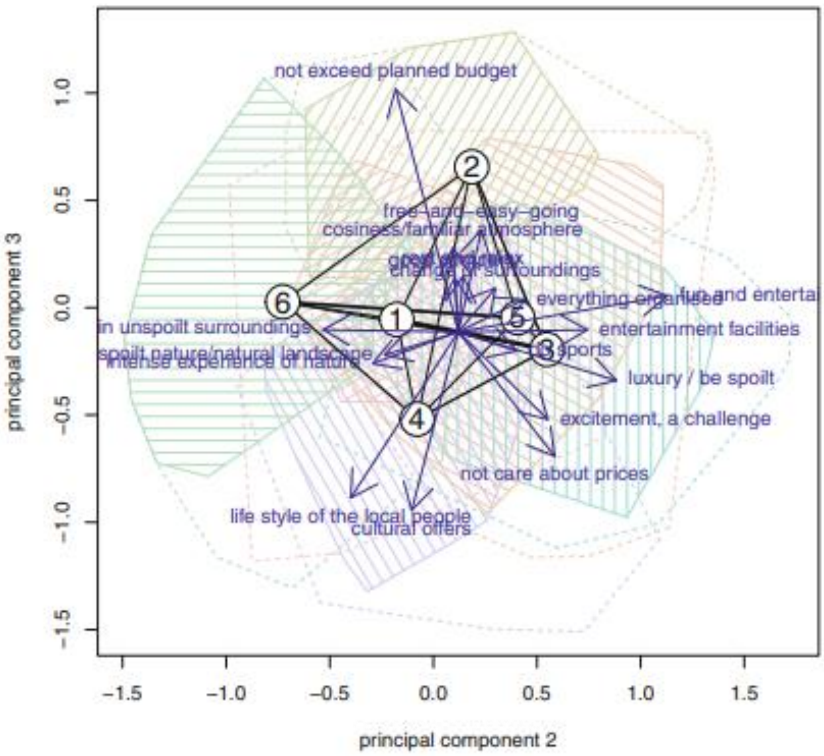

Fig. 8.6 Segment separation plot using principal components 2 and 3 for the Australian travel motives data set without observations

It's important to note that each segment separation plot represents only one possible projection, and the interpretation of segment overlap should consider multiple projections.

Step 7: Describing Segments

7.1 Using Visualisations to Describe Market Segments

Graphical statistics offer two significant advantages when it comes to describing market segments. Firstly, they simplify the interpretation of results for both data analysts and users, making it easier to understand the findings. Secondly, graphical statistics integrate information on the statistical significance of differences, preventing the over-interpretation of insignificant variations. This ensures that only meaningful distinctions are highlighted, providing a more accurate representation of the data. By employing different chart types suited for nominal/ordinal and metric descriptor variables, such as gender or age, graphical statistics effectively visualize differences, aiding in the comprehensive analysis and communication of market segments.

Nominal and Ordinal Descriptor Variables

Nominal and ordinal descriptor variables play a crucial role in market segmentation. Nominal variables represent categories without any inherent order, such as gender, country of origin, or product brand. These variables help in dividing the market into distinct segments based on different characteristics or preferences. Ordinal variables, on the other hand, possess a natural order or ranking, but the intervals between the values may not be uniform. Examples of ordinal variables include education level (e.g., high school, bachelor's degree, master's degree) or customer satisfaction ratings (e.g., very dissatisfied, neutral, very satisfied). These variables enable the creation of segments based on different levels or rankings, allowing for a more refined analysis of customer preferences and behaviour. By utilizing nominal and ordinal descriptor variables in market segmentation, businesses can gain insights into customer demographics, preferences, and behaviours. This information helps in tailoring marketing strategies, developing targeted products or services, and effectively reaching specific customer segments. Visualizing these variables through graphical statistics further enhances the understanding and interpretation of market segment differences, aiding in decision-making and resource allocation.

Metric Descriptor Variables

Metric descriptor variables are an essential component of market segmentation analysis. These variables represent measurable quantities with a specific scale and meaningful numerical values. They provide precise quantitative data that can be used to understand and segment the market based on various metrics. Examples of metric descriptor variables commonly used in market segmentation include age, income, number of purchases, customer lifetime value, or frequency of product usage. These variables offer valuable insights into customer behaviors, preferences, and purchasing power. By analyzing metric descriptor variables, businesses can identify distinct market segments with similar characteristics or behaviors. This information enables companies to develop targeted marketing strategies, pricing models, product features, and distribution channels tailored to specific customer segments. Visualizing metric descriptor variables through graphical statistics allows for a comprehensive and intuitive representation of market segment differences. It enables analysts to identify patterns, trends, and relationships between variables, facilitating data-driven decision-making. Graphical representations such as histograms, scatter plots, or box plots provide visual cues that aid in understanding the distribution, central tendencies, and variances within different market segments based on metric variables.

Testing for Segment Differences in Descriptor Variables

Simple statistical tests can be used to formally test for differences in descriptor variables across market segments. The simplest way to test for differences is to run a series of independent tests for each variable of interest. The outcome of the segment extraction step is segment membership, the assignment of each consumer to one market segment. Segment membership can be treated like any other nominal variable. It represents a nominal summary statistic of the segmentation variables. Therefore, any test for association between a nominal variable and another variable is suitable.

Predicting Segments from Descriptor Variables

Another way of learning about market segments is to try to predict segment membership from descriptor variables. To achieve this, we use a regression model with the segment membership as categorical dependent variable, and descriptor variables as independent variables.

Binary Logistic Regression

We can formulate 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 choosing the logit link that maps the success probability.

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 Models

Classification and regression trees (CARTs) are a supervised learning technique used for predicting binary or categorical dependent variables based on a set of independent variables. CARTs offer several advantages, including variable selection, ease of interpretation through visualizations, and the ability to incorporate interaction effects. They can handle many independent variables and work well for segmenting consumer data. However, a disadvantage of CARTs is that they can produce unstable results, where small changes in the data can lead to entirely different trees. The process of building a CART involves a stepwise procedure where consumers are split into groups based on an independent variable. The goal of these splits is to create groups that are as pure as possible in terms of the dependent variable. The resulting tree consists of nodes representing each split and terminal node that are not further divided. Segment membership can be predicted by traversing the tree, moving down the branches based on the consumer's independent variable values until reaching a terminal node. The predicted segment membership is based on the segment memberships of consumers in that terminal node. Overall, CARTs provide a useful approach for segmenting data and predicting categorical outcomes, offering interpretability and flexibility, although their results can be sensitive to small changes in the data.

Step 8: Selecting the Target Segment

8.1 The Targeting Decision

In Step 8, the selection of one or more target market segments is required. First, the remaining segments must pass the knock-out criteria test. Then, the attractiveness of the segments and their competitiveness for the organization is evaluated. The segmentation team asks two categories of questions:
1. Which segment does the organization prefer to target and commit to?
2. Which organization offering the same product does each segment prefer? How likely is it that our organization would be chosen and committed to? Answering these questions forms the basis of the target segment decision.

8.2 Market Segment Evaluation

Using a decision matrix to visualize segment attractiveness and organizational competitiveness is recommended. The matrices help evaluate market segments and select target segments. The market segmentation team decides which variation of the decision matrix provides the most useful framework for decision making. The matrix plots two criteria: segment attractiveness and relative organizational competitiveness for each segment.

Segment Evaluation Plot

Segment attractiveness and organizational competitiveness cannot be measured by a single criterion. Users should refer to their specifications of an ideal target segment. Step 2 of market segmentation analysis defines the ideal target segment and determines criteria and their respective weights. In Step 8, the missing information needed to select a target segment is the actual value of each segment for the specified criteria, which is obtained through grouping, profiling, and description. The location of each segment in the evaluation plot is calculated by multiplying the weight of the attractiveness criterion with the segment's value. The summed weighted values represent the segment's overall attractiveness plotted along the x-axis.
The same procedure is applied to measure relative organizational competitiveness. When selecting criteria, the question is: Which criteria do consumers use to choose between market offers? Possible criteria include product attractiveness based on desired benefits, price suitability, distribution channel availability, and segment awareness of the organization's brand image. The calculation of each segment's value on the "How attractive are we to the segment?" axis follows the same process as segment attractiveness: agreeing on criteria, assigning weights, rating each segment, and multiplying and summing the values.
The bubble size on the plot can represent various factors. Usually, profit potential is plotted, combining segment size and spending. Profit is crucial when selecting target segments. However, in different contexts, alternative criteria may be significant. For instance, a non-profit organization using market segmentation to recruit volunteers for land regeneration may choose to plot the number of volunteered hours as the bubble size.

Step 9: Customising the Marketing Mix

9.1 Implications for Marketing Mix Decisions

Originally, marketing was seen as a toolbox for selling products, with marketers using various tools to achieve sales success. Borden identified 12 key elements of this toolbox, including product planning, packaging, distribution channels, pricing, personal selling, branding, advertising, and more. Over time, the concept of marketing mix evolved, with the commonly accepted 4Ps: Product, Price, Promotion, and Place. Market segmentation is not a standalone marketing strategy but is closely intertwined with other strategic elements like positioning and competition. The segmentation-targeting-positioning (STP) approach recognizes this relationship. The STP approach follows a sequential process: segmenting the market, selecting a target segment, and then positioning the product to meet the segment's needs and stand out from competitors.

While it is beneficial to view market segmentation as the initial step in the STP approach, it's important to remain flexible. Sometimes it may be necessary to revisit segmentation and targeting before committing to specific target segments in the long term.

To maximize the benefits of market segmentation, it's crucial to customize the marketing mix for the target segment. This involves adapting products, prices, distribution channels, and promotional strategies to suit the specific segment.

One approach is to base the segmentation analysis on one of the 4Ps. For pricing decisions, variables like price sensitivity and deal proneness are relevant. Advertising decisions can be informed by benefits sought, lifestyle, and psychographic variables. For distribution decisions, store loyalty, patronage, and store selection preferences are valuable. However, market segmentation analysis is often not focused on a single 4P. Instead, the insights gained from describing the target segment guide the organization in developing or adjusting the marketing mix to effectively serve that segment.

9.2 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.

9.3 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.

9.4 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.

9.5 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.

Replication of McDonalds Case Study in Python

https://github.com/dipak141/McDonald-Case-study - Dipak Chandra Singha

https://github.com/Ajay2135/ajay_mcdonalds_code_conversion - S Ajay

https://github.com/AshDDftw/Mcdonalds_case_study - Ashudeep Dubey

https://github.com/ankitdhadave/fn_lab - Ankit Moreshwarrao Dhadave

https://github.com/Sinha532/McDonalds_CaseStudy - Lokesh Sinha N