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Market Segmentation Analysis

GitHub:- https://github.com/shubhkh/Feynn_Labs_Intern/tree/main/Task_2

Step 1 :- Deciding (not) to segment

Why is it important?

Market Segmentation is necessary as:

1. Better understanding of customers: Market segmentation allows businesses to gain a better understanding of their customers by identifying their specific needs, preferences, and behaviors. This enables businesses to tailor their marketing messages and product offerings to better meet these needs, ultimately leading to more satisfied and loyal customers.
2. Improved marketing effectiveness: By targeting specific consumer groups with tailored marketing messages andproduct offerings, businesses can increase the effectiveness of their marketing campaigns. This leads to better engagement, higher response rates, and increased sales.
3. Competitive advantage: Market segmentation allows businesses to differentiate themselves from their competitors by creating products and marketing messages that are more tailored to the needs and preferences of specific consumer groups. This helps businesses to stand out in a crowded market and gain a competitive advantage.
4. Efficient use of resources: By targeting specific consumer groups, businesses can use their marketing resources more efficiently. Rather than spending resources on marketing campaigns that target a broad audience, businesses can focus their resources on campaigns that are more likely to resonate with specific consumer groups.

Types of Market Segmentation

There are different types of market segments that you can create. The four major types of Market Segmentation are givenbelow.

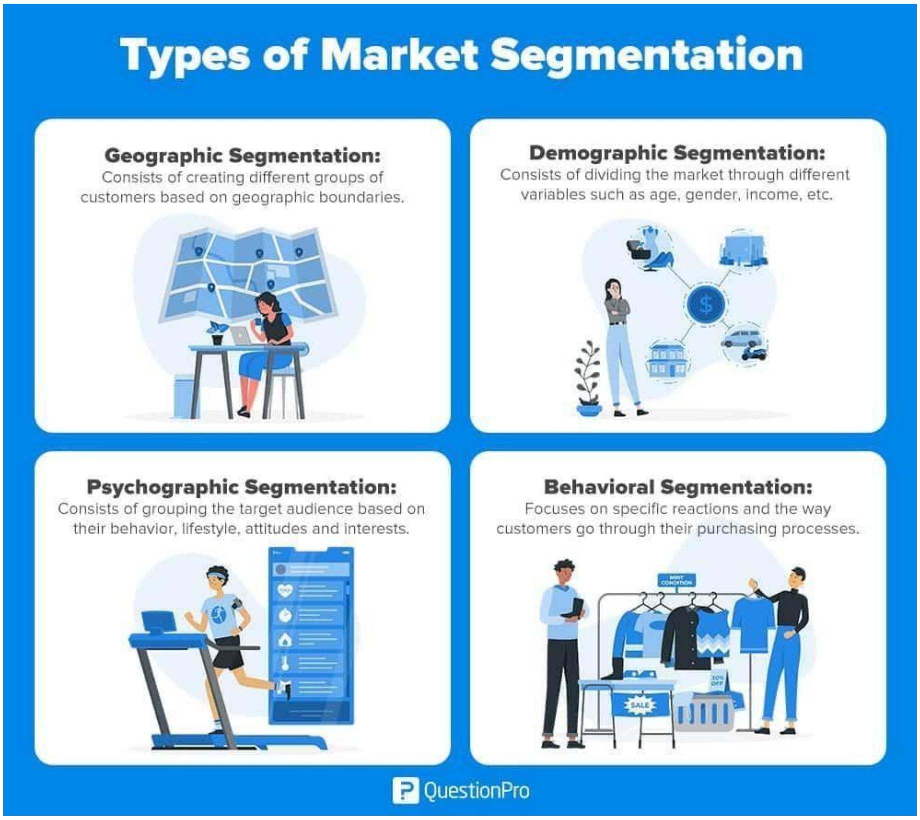


Fig: Methods of Market Segmentation

Geographic Segmentation

Dividing the market based on geographic location such as country, region, city, or climate. Geographic Segmentation splits up your target segment based on locations such as country, stateetc. Customers can also be identified by taking into account the characteristics of the area they live in for example language, urban, suburban, rural etc.

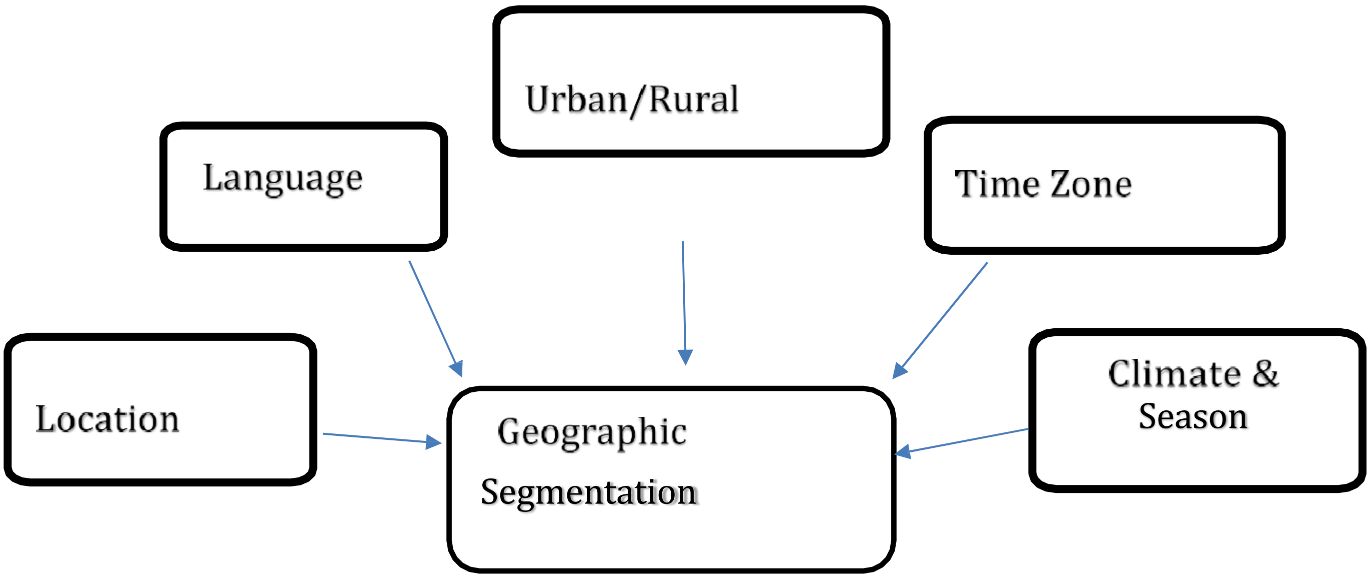


Fig: Geographic Segmentation.

Demographic Segmentation

Dividing the market based on demographic characteristics such as age, gender, income, education, occupation, marital status, and family size.

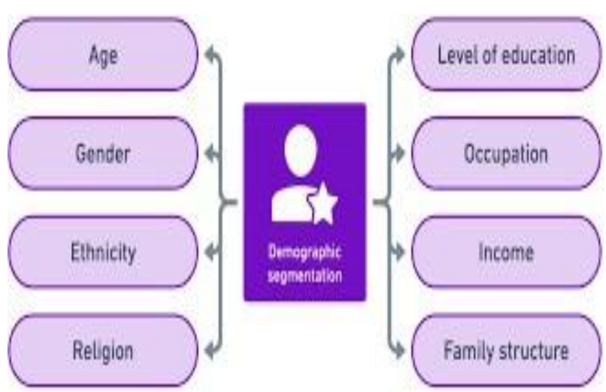


Fig: Demographic Segmentation.

Psychographic Segmentation

Psychographic Segmentation splits the target market based on characteristics that are mental andemotional. Some examples of psychographic characteristics include personality traits, interests, beliefs, values, attitudes and lifestyles.

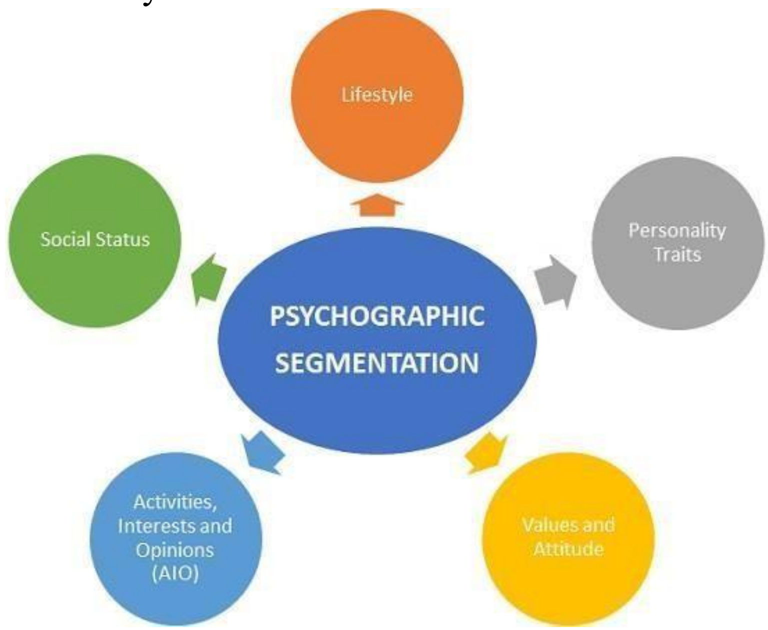
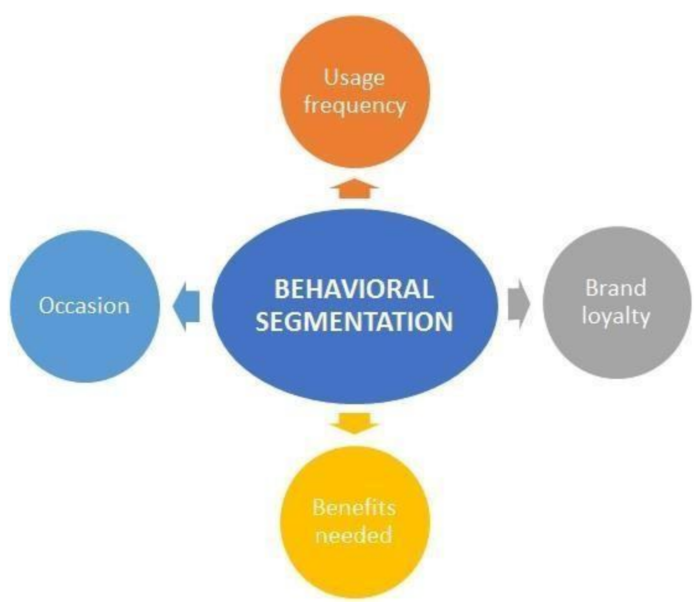


Fig: Psychographic Segmentation

Behavioral Segmentation

Behavioral segmentation is a form of marketing segmentation that divides the target market based on behavioral patterns exhibited. This segmentation type studies the behavioral traits of consumers — their knowledge of, attitude towards, use of, likes/dislikes of, or response to a product, service, promotion, or brand.



The How

Following are the key points involved in Market Segmentation.

Data exploration

It is the first step of data analysis used to explore and visualize data to uncover insights from thestart or identify areas or patterns to dig into more. Data exploration is the process of investigating, understanding, and analyzing data to uncover patterns, relationships, and insights that can help inform decision-making. This involves using various tools and techniques to visualize, summarize, and explore data sets in order to better understand the underlying trends and patterns that may exist within them.

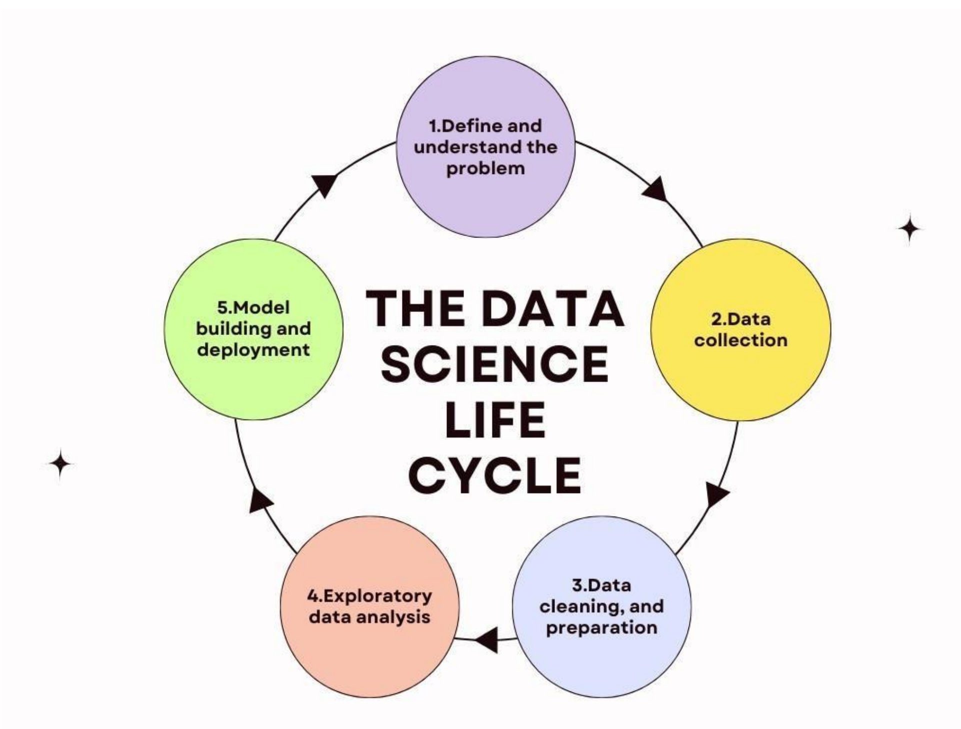
Results from the data exploration stage provide insights into the suitability of differentsegmentation methods for extracting market segments.

Data cleaning

Data cleaning, also known as data cleansing or data scrubbing, is the process of identifying and correcting or removing errors, inconsistencies, and inaccuracies from data sets. The goal of data cleaning is to improve the quality and accuracy of data so that it can be used effectively for analysis, modeling, and decision-making.

Data cleaning typically involves several steps, including:

1. Identifying and removing duplicate data.
2. Identifying and correcting data that is missing or incomplete.
3. Identifying and correcting data that is inaccurate or inconsistent.
4. Converting data to a standardized format.
5. Removing irrelevant or outdated data.
6. Handling outliers or data points that are significantly different from the rest of the data.



Data Preprocessing

Numerical Variables
Numeric variables are often on different scales and cover different ranges, so they can't be easilycompared. What's more, variables with large values can dominate those with smaller values when using certain modelling techniques. centring and scaling is a common pre-processing task that puts numeric variables on a common scale so no single variable will dominate the others.
The simplest way to centre data is to subtract the mean value from each data point. Subtracting the mean centres, the data around zero and sets the new mean to zero.

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 variablesto numeric ones, if it makes sense to do so Exploring Data Merging levels of categorical variables is useful if the original categories are too differentiated (too many).

Descriptive Analysis
Descriptive Analysis is the type of analysis of data that helps describe, show, or summarize datapoints in a constructive way such that patterns might emerge that fulfills every condition of the data. It is one of the most important steps for conducting statistical data analysis. The three main types of descriptive statistics are frequency distribution, central tendency, and variability of a data set. The frequency distribution records how often data occurs, central tendency recordsthe data's centre point of distribution, and variability of a data set records its degree of dispersion. Helpful graphical methods for numeric data are histograms, box-plots, and scatter plots. Bar plots of frequency counts are useful for the visualization of categorical variables.

Principal Components Analysis
Principal component analysis, or simply PCA, is a dimensionality-reduction method that is often used to reduce the dimensionality of large data sets, by transforming a large set of variables into a smaller one that still contains most of the information in the large set. Reducingthe number of variables of a data set naturally comes at the expense of accuracy, but the trick in dimensionality reduction is to trade a little accuracy for simplicity. Because smaller data sets areeasier to explore and visualize and make analyzing data much easier and faster for machine learning algorithms without extraneous variables to process. The first variable (principal component) contains most of the variability, the second principal component contains the second most variability, and so on.

The Elbow Method

Finding the ideal number of clusters to divide the data into is a critical stage in any unsupervised technique. One of the most prominent techniques for figuring out this ideal value of k is the elbow approach. It is probably the most well-known approach which involves calculating the sum of squares for each cluster size, graphing the results, and identifying the ideal cluster size by looking for an elbow where the slope changes from steep to shallow.

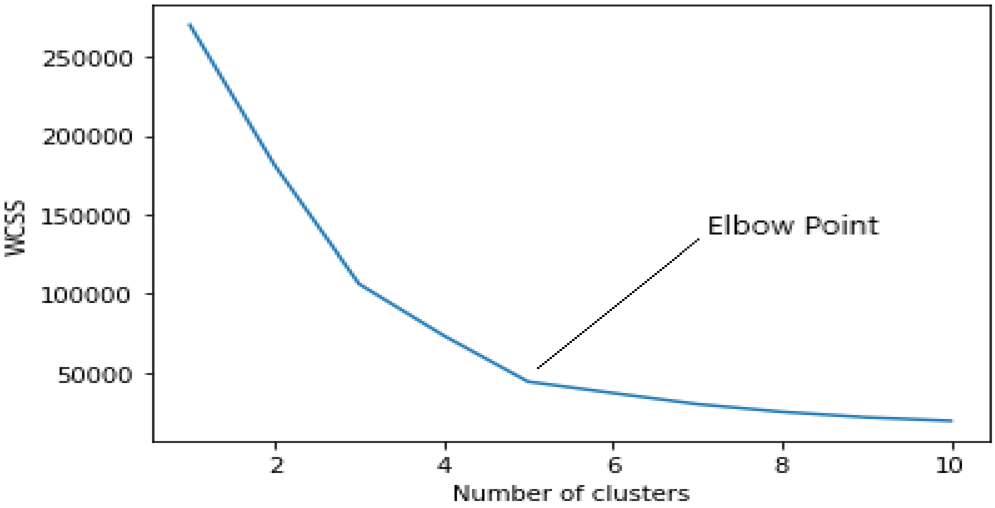


Fig: The Elbow Method

Why to use this algorithm?

Each feature of the data could have varied values, increasing the overall variance of the feature.The main goal is to segment our data based on like-values features. Clustering algorithms separate the data into clusters basedon their values, i.e. values belonging to a similar range willbe assigned to the same cluster.

Advantages of K-Means

ClusteringRelatively simple

to implement Scales to large

data sets Guarantees

convergence

Generalises clusters to different shapes and sizes, such as elliptical clusters

The image below shows the Clustering Algorithm repeated for several iterations until minimum sum ofvariance of each cluster is achieved.

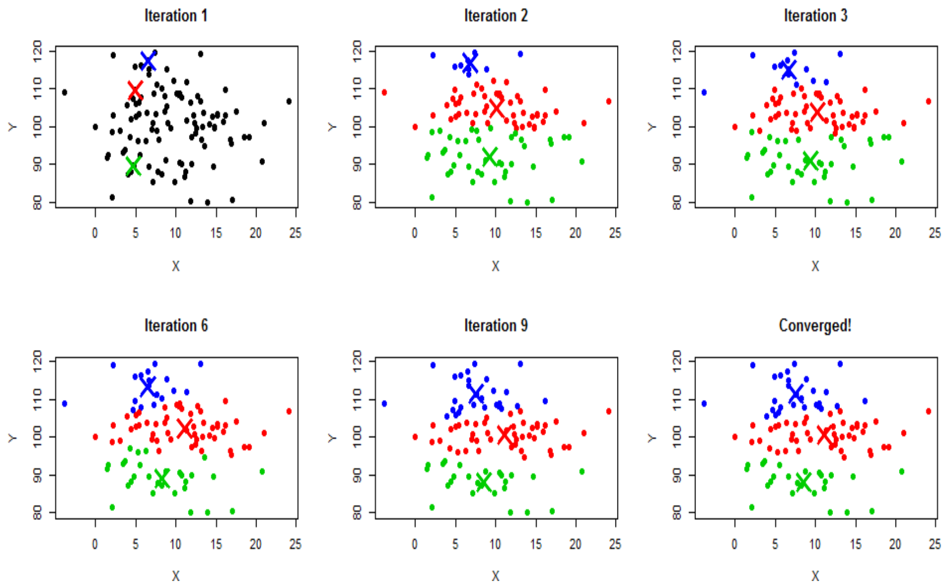


Fig: K-Means Clustering in action

Knock-Out Criteria

Knock-out criteria are used to determine if market segments resulting from the market segmentation analysis qualify to be assessed using segment attractiveness criteria. The first set of such criteria includes :

- Sustainability
- Measurability
- Accessibility

Additional criteria recommended that fall into Knock-out criteria category :

- **The segment must be homogenous;** members of segment must be similar to one another.
- **The segment must be distinct;** members of segment must be distinctly differ-ent from membersof other segments.
- **The segment must be large enough;** the segment must contain enough con-sumers to make itworthwhile to spend extra money on customising the

market-ing mix for them.

- **The segment must be matching the strengths of the organisation;** theorganisation must have thecapability to satisfy segment members' needs.
- **Members of the segment must be identifiable;** it must be possible to spot them in the marketplace.
- **The segment must be reachable;** there has to be a way to get in touch with members of thesegment in order to make the customized marketing mix accessi-ble to them.

Knock-out criteria must be understood by senior management, the segmentation team, and the advisory committee. Most of them do not require further specification, but some do. For example, while size is non- negotiable, the exact minimum viable target segment size need to be specified.

Attractiveness Criteria

Attractiveness criteria are not binary in nature. Segments are not assessed as either complying or not complying with attractiveness criteria. Rather, each market segment is rated; it can be more or less attractive with respect to a specific criterion. The at-tractiveness across all criteria determines whether a market segment.

Implementing a Structured Process

The most popular structured approach for evaluating market segments in view of se-lecting them as target markets is the use of a segment evaluation plot showing segment attractiveness along one axis, and organisational competetiveness on the other axis.
Factors which constitute both segment attractiveness and organizational competitive-ness need to be negotiatedand agreed upon. To achieve this, a large number of possi- ble criteria has to be investigated before agreementis reached on which criteria are the most important for the organisation. At the end of this step, the market segmentation team should have a list of approximately six segment attractiveness criteria. Each of these criteria should have a weight attached to it to indicate how important it is to the organisation compared to the other criteria.

Step-3: Collecting Data

Segmentation Variables

Empirical data forms the basis of both commonsense and data-driven market segmentation. Empirical data is used to identify or create market segments and – later in the process – describe these segments in detail. The term segmentation variable refers to the variable in the empirical data used in commonsence segmentation split the sam- ple into market segments. In commonsence segmentation, the segmentation variable
is typically on single characteristic of the consumers in the sample (as shown in below Fig. . .)

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

Figure 4: *Gender as a possible segmentation variable in commonsense market segmen-tation*

Each row in this table represents on consumer, each variable represents one charac- teristic of that consumer. An entry of 1 in the data set indicates that the consumer has that characteristic. An entry of 0 indicates that the consumer does not have that characteristic. The commonsense segmentation illustrated in Fig-4 uses gender as the segmentation variable. All the other personal characteristics available in the data – in this case: age, the number of vacations taken, and information about five benefits people seek or do not seek when they go on vacation – serve as so-called **descriptorvariables**. They are used to describe the segments in detail.

The difference between commonsense and data-driven market segmentation is that data-driven market segmentation is based not on one, but on multiple segmentation variables. These segmentation variables serve as the starting point for identifying nat- urally existing, or artificially creating market segments useful to the organisation (as shown in below Fig).

Sociodemographics		Travel behaviour	Benefits sought				
gender	age	N° of vacations	relaxation	action	culture	explore	meet people
Female	34	2	1	0	1	0	1
Female	55	3	1	0	1	0	1
Male	87	2	1	0	1	0	1
Female	68	1	0	1	1	0	0
Female	34	1	0	0	1	0	0
Female	22	0	1	0	1	1	1
Female	31	3	1	0	1	1	1
Male	55	4	0	1	0	1	1
Male	43	0	0	1	0	1	0
Male	23	0	0	1	1	0	1
Male	19	3	0	1	1	0	1
Male	64	4	0	0	0	0	0
descriptor variables			segmentation variables				

Figure 5: *Segmentation variable in data-driven market segmentation*

When commonsense segments are extracted – even if the nature of the segments isknown in advance –data quality is critical to both assigning each person in the sample to the correct market segment, and being able to correctly describe the segments.

The same holds for data-driven market segmentation where data quality deter- mines the quality of the extracted data-driven market segments, and the quality of the de- scriptions of the resulting segments. Good market segmentation analysis requires good empirical data.

Geographic Segmentation

Geographic information is seen as the original segmentation criterion used for the pur-pose of market segmentation. Typicallynwhen geographic segmentation is used the consumer's location of residence serves as the only criterion to form marketsegments.

The **key advantage** of geographic segmentation is that each **consumer can easily be assigned to a geographic unit**. As a consequence, it is easy to target communi- cation messages, and select communication channels (such as local newspapers, local radio and TV stations) to reach the selected geographic segments.

The **key disadvantage** is that living in the same country or area does not necessarilymean that people share other characteristics relevant to marketers, such as benefits they seek when purchasing a product.
Despite the potential shortcomings of using geographic information as the segmenta- tion variable, the location aspect has experienced a revival in international market segmentation studies aiming to extract market segments across geographic boundaries. Such an approach is challenging because the segmentation variable(s) must be mean- ingful across all the included geographic regions, and becauseof the known biases that can occur if surveys are completed by respondents from different cultural backgrounds.

Socio-Demographic Segmentation

Typical socio-demographic segmentation criteria include age, gender, income and ed- ucation. Socio- demographic segments can be very useful in some industries. For ex- ample: luxury goods (associated with high income), cosmetics (associated with gen- der; even in times where men are targeted, the female and male segments are treated distinctly differently), baby products (associated with gender), retirement villages (as- sociated with age), tourism resort products (associated with having small children or not).
As is the case with geographic segmentation, socio-demographic segmentation crite- ria have the advantage that segment membership can easily be determined for every consumer. In some instances, the socio-demographic criterion may also offer an expla- nation for specific product preferences (having children, for example, is the actual rea- son that families choose a family vacation village where previously, as a couple, their vacationchoice may have been entirely different). But in many instances, the socio- demographic criterion is not the cause for product preferences, thus not providing suffi- cient market insight foroptimal segmentation decisions.

Step 5: Extracting Segments

Market segmentation analysis using consumer data is exploratory and the results obtained depend on the assumptions made about the structure of the segments. Consumer preferences are spread across the entire plot and extracting market segments requires the use of clustering methods. The selection of a suitable clustering method depends on the context-dependent requirements desired by the researcher. It is important to explore market segmentation solutions derived from different clustering methods and understand how algorithms impose structure on the extracted segments.

The aim is to discuss the given text is to provide an overview of the most popular extraction methods used in market segmentation and point out their specific tendencies of imposing structure on the extracted segments. The chapter discusses different algorithms and methods for extracting market segments from consumer data and highlights that there is no single best algorithm for all data sets. Rather, each method has its advantages and disadvantages, and investigating and comparing alternative segmentation solutions is critical to arriving at a good final solution. The chapter also emphasizes that data characteristics and expected or desired segment characteristics allow a pre-selection of suitable algorithms to be included in the comparison. Behavioral segmentation refers to the classification of consumers based on their behaviors toward a product, service, or brand. It involves using data on consumer purchase behavior, usage behavior, and other relevant behavioral information to identify groups of consumers with similar behavior patterns. There are several types of behavioral segmentation, including occasion segmentation, benefit segmentation, loyalty segmentation, and usage rate segmentation. Occasion segmentation involves dividing the market based on the specific occasions or situations in which consumers use the product or service. Benefit segmentation involves dividing the market based on the specific benefits or needs that consumers seek from the product or service. For example, a company that sells laptops may target students who need a lightweight laptop for school, while also targeting professionals who need a powerful laptop for work. Loyalty segmentation involves dividing the market based on the loyalty of customers to the brand or product. For example, a company may target its most loyal customers with special offers or rewards to encourage repeat purchases. Usage rate segmentation involves dividing the market based on the frequency or volume of product usage. For example, a company may target heavy users of a product with loyalty programs or incentives, while also targeting light users with promotions to encourage increased usage.

This passage discusses the importance of selecting appropriate variables for market segmentation analysis. In data-driven segmentation, all variables relevant to the construct captured by the segmentation criterion need to be included, while unnecessary variables must be avoided. Including unnecessary variables can make questionnaires long and tedious for respondents, which, in turn, causes respondent fatigue. The presence of noisy variables can also prevent algorithms from identifying the correct segmentation solution. Noisy variables can result from not carefully developing survey questions or not carefully selecting segmentation variables from among the available survey items. The passage recommends conducting exploratory or qualitative research to develop a good questionnaire, ensuring that no critically important variables are omitted. The passage also discusses the importance of response options provided to respondents in surveys, which determine the scale of the data available for subsequent analyses. Preferably, either metric or binary response options should be provided to respondents if those options are meaningful with respect to the question asked. Using binary or metric response options prevents subsequent complications relating to the distance measure in the process of data-driven segmentation analysis.

The section explains the use of normal distributions in market segmentation. Normal distributions are used to model the covariance between variables in metric data. The multivariate normal distribution is used when there are multiple variables that have an approximate univariate normal distribution and are not independent of each other. The segment-specific parameters for the multivariate normal distribution are the combination of the mean vector and the covariance matrix. The number of parameters to estimate is $p + p(p + 1)/2$.

The mixture of normal distributions can be illustrated using the artificial mobile phone data set. The package "mclust" in R is used to fit models for different numbers of segments using the EM algorithm. The BIC is used to recommend extracting three segments. An uncertainty plot is used to illustrate the ambiguity of segment assignment. The further away from 1 a consumer’s maximum segment assignment probability is, the less certain is the segment assignment. The uncertainty plot is useful for alerting the data analyst to solutions that do not induce clear partitions and pointing to market segments that are artificially created.

For two-dimensional data, each market segment can be shaped like an ellipse, with ellipses having different shapes, areas, and orientations. The ellipse corresponding to one market segment could be very flat and point from bottom left to top right, while another one could be a perfect circle.

Australian Vacation Motives

The example provided showcases the use of model-based clustering methods, specifically the Mclust package in R, to identify segments within a dataset of vacation motives and behaviors. The data consisted of metric variables, including moral obligation score, NEP score, and environmental behavior score on vacation. After removing missing values, the Mclust package was used to fit a mixture model with varying covariance matrices and select the best model using the Bayesian Information Criterion (BIC). The analysis revealed that a mixture model with two segments was selected when all 14 different covariance matrices were considered, while a model with three segments emerged when only covariance models with equal volume, shape, and orientation were used. The best models were visualized using classification plots, which showed the segments and their assigned data points. The example highlights the importance of considering the underlying structure of the data when clustering, as model-based methods allow for more flexible and nuanced clustering compared to traditional methods like k-means clustering. Additionally, model-based clustering can provide more information about the segments beyond just their means, such as their covariance matrices and segment sizes.

The convex hull of a set of observations in two-dimensional space is a closed polygon connecting the outer points in a way that ensures that all points of the set are located within the polygon. To generate a coloured scatter plot of the data with convex hulls for the segments, one can use the function clusterhulls() from package MSA. When using the k-means algorithm for segmentation, specifying the number of clusters (number of segments) can be difficult as consumer data typically does not contain distinct, well-separated naturally existing market segments. One approach is to repeat the clustering procedure for different numbers of market segments and compare the sum of distances of all observations to their representative across those solutions. The lower the distance, the better the segmentation solution. To select the best solution for each number of segments, 10 runs of the k-means algorithm are calculated for each number of segments using different random initial representatives (nrep = 10). The number of segments varies from 2 to 8.

Global stability analysis and segment level stability analysis are two techniques used to assess the stability and reliability of segmentation solutions in market segmentation. Global stability analysis involves conducting multiple segmentations using different samples of the same data and evaluating the stability of the resulting segments. The idea is to determine whether the segmentation solution is stable across different samples, indicating that the segments are robust and reliable. The most common method for conducting global stability analysis is the split-half method, where the data is randomly split into two halves, and each half is separately segmented. The resulting segments are then compared to assess the stability of the solution. Segment level stability analysis, on the other hand, involves assessing the stability of individual segments across different samples. This is done by examining the consistency of segment membership across different samples. For example, if a segment consists of similar individuals across different samples, then it is considered stable and reliable. Segment level stability analysis is particularly useful for identifying promising segments that are consistent and robust across different samples. Together, global stability analysis and segment level stability analysis can be used to identify promising segmentation solutions and promising segments. A segmentation solution that is stable across different samples and produces consistent segments is more likely to be reliable and accurate. Similarly, segments that are stable across different samples are more likely to be useful and relevant for marketing purposes.

Step 6: Profiling Segments

Identifying Key Characteristics of Market Segments :

The aim of this step - profiling segments is to get to know the generated segments from the extraction step. Profiling consists of characterising the market segments individually, but also in comparison to the other market segments.

Segment Profiling with Visualisations :

Demonstrating the segmented customers visually is considered as a much better alternative to long explanations. They are much easier to interpret and process and finally make critical decisions.

A segment profile plot is used to understand the defining characteristics of each segment. Itis also called a panel-plot. Each panel represents a segment. For each segment, the segment profile plot shows the cluster centres (centroids, representatives of the segments).An example of a panel plot is shown below :

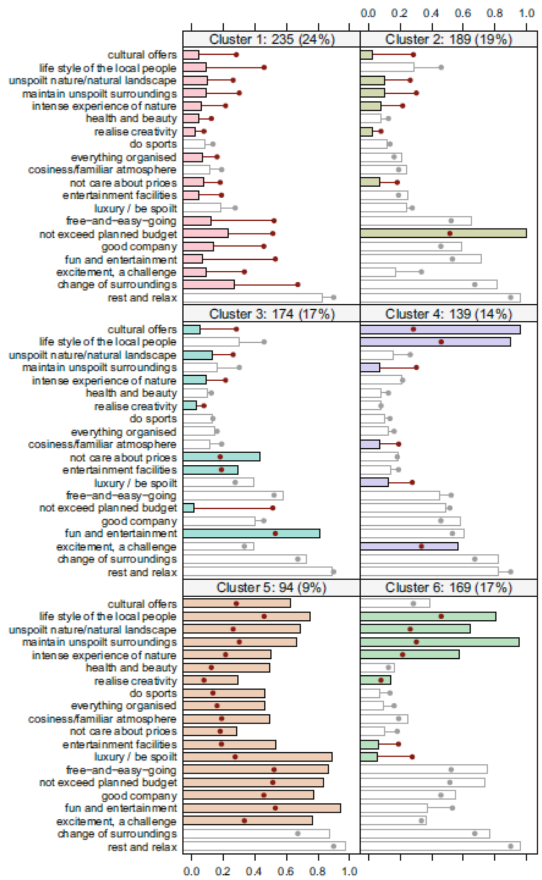


Fig. 8.2 Segment profile plot for the six-segment solution of the Australian travel motives data set

Different panel and different segment have different centroids and distributions representing different kind of customers prioritizing different motives for travelling.

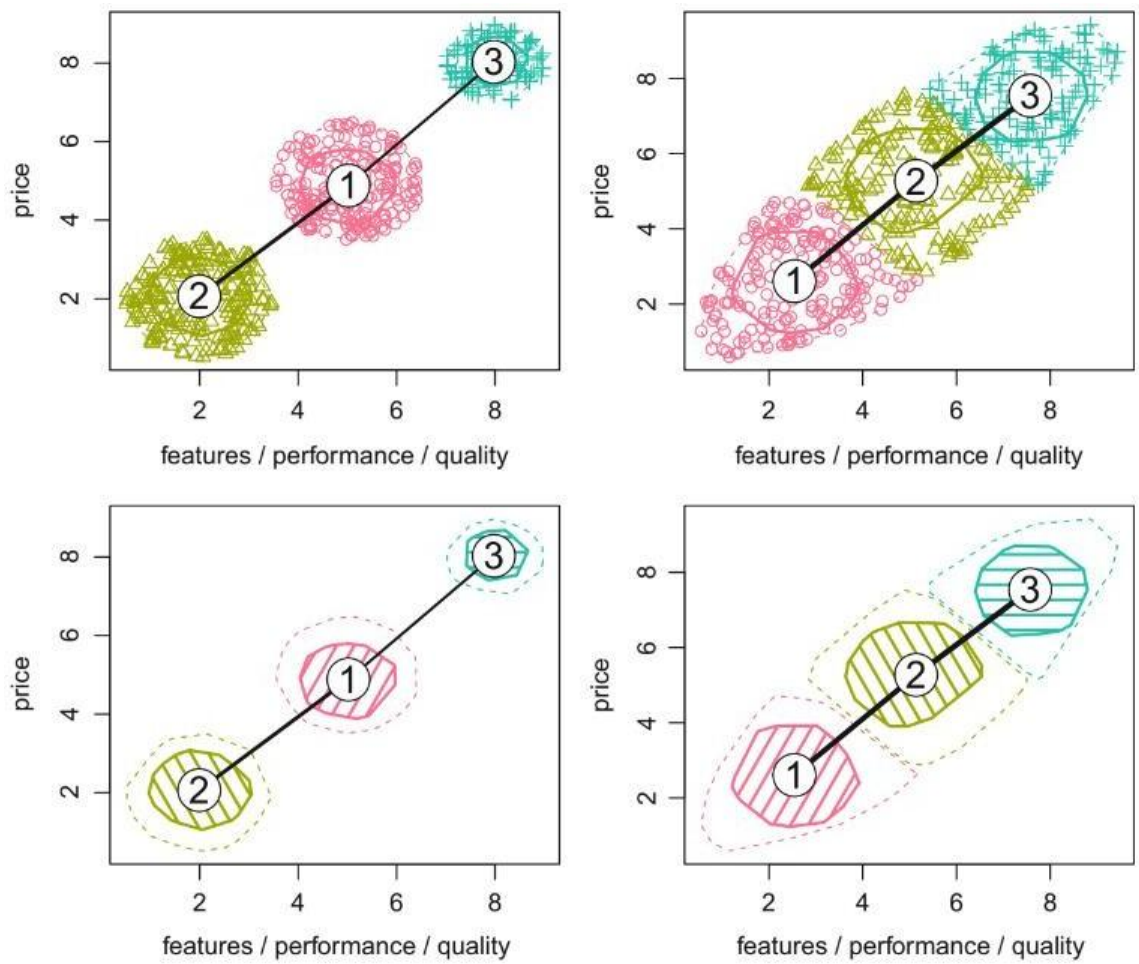


Fig. 8.4 Segment separation plot including observations (first row) and not including observations (second row) for two artificial data sets: three natural, well-separated clusters (left column); one elliptic cluster (right column)

The graphs on the RHS are closely packed because two datasets are used in their segmentation. To avoid this problem, we can perform principal component analysis which reduces multiple dimensions to a smaller number of dimensions.

Step 7: Describing Segments

In step 7, we try to describe the segments using additional information like the consumer's age, gender, past travel behaviour, 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 chart and mosaic chart.

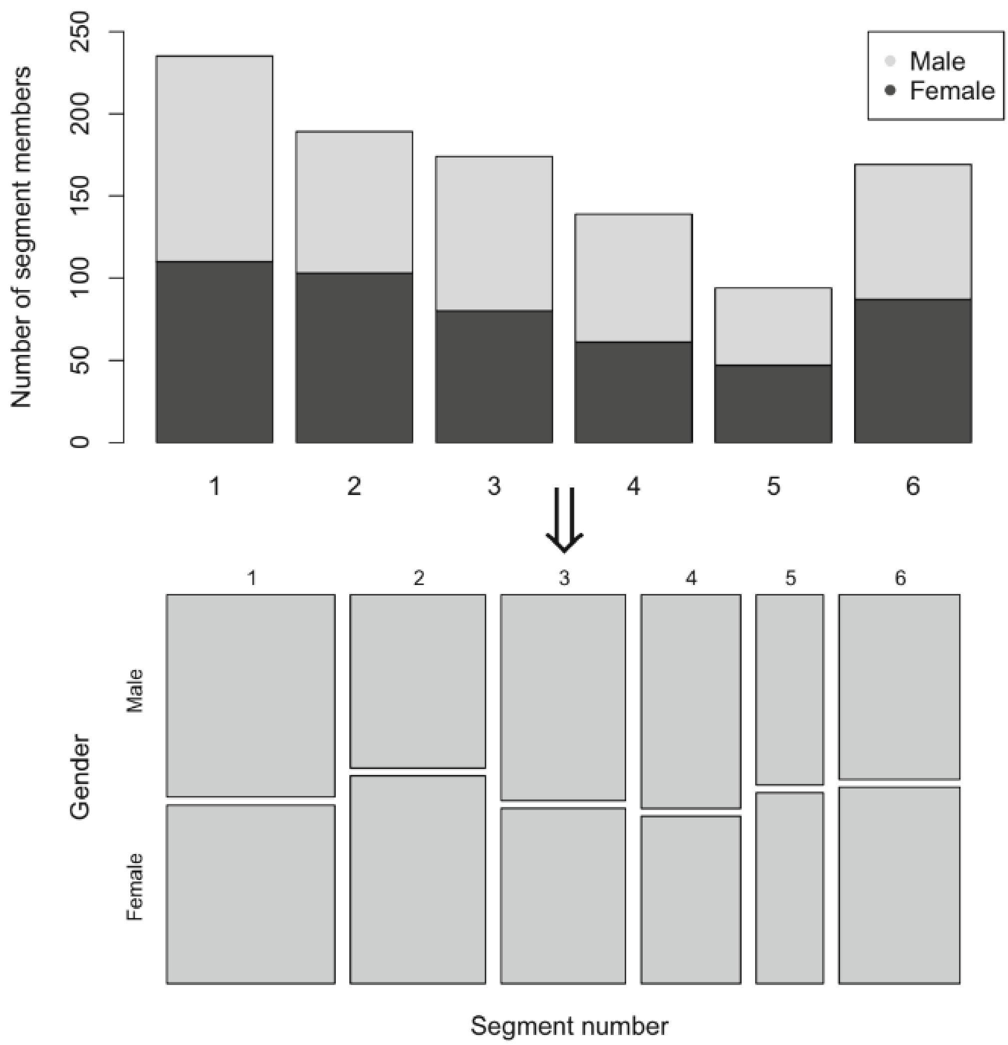


Fig. 9.1 Comparison of a stacked bar chart and a mosaic plot for the cross-tabulation of segment membership and gender for the Australian travel motives data set

Mosaic plots can also be encoded with colour combinations for better representation.

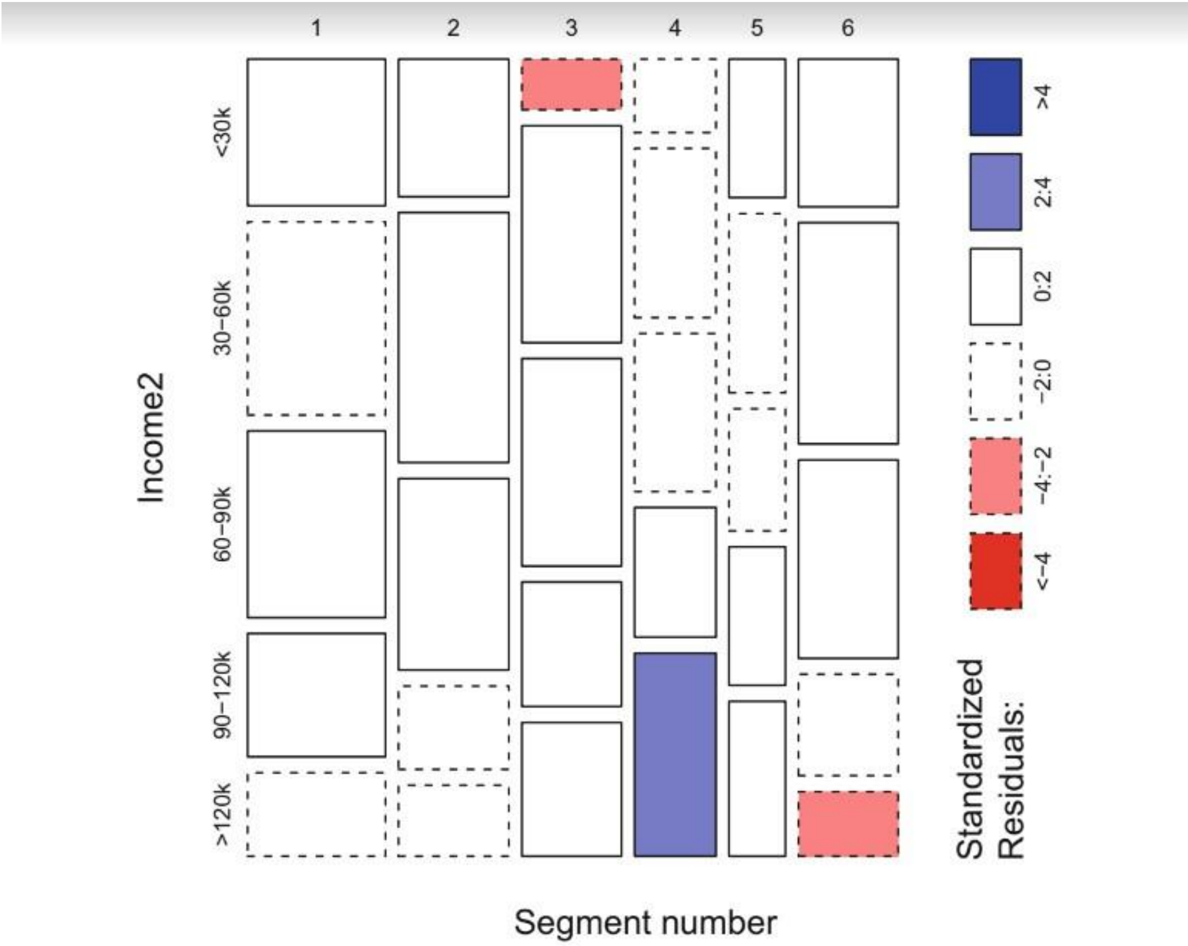


Fig. 9.3 Shaded mosaic plot for cross-tabulation of segment membership and income for the Australian travel motives data set

Metric Descriptor Variables :

The variables are of continuous numeric data type. Examples include age, number of nights at the tourist destinations, money spent on accommodation.

The best representation of these variables is done by histograms.

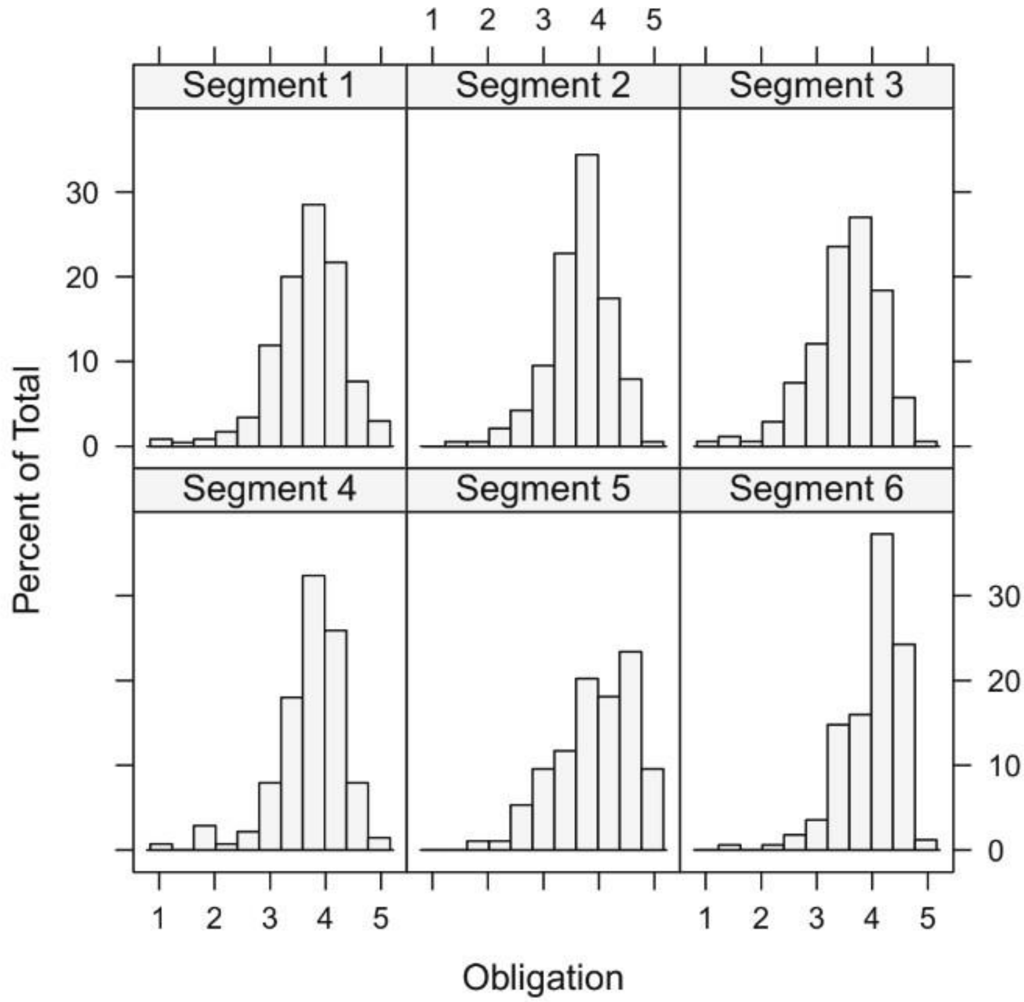


Fig. 9.6 Histograms of moral obligation to protect the environment by segment for the Australian travel motives data set

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 remain constant.

$$y = \beta_0 + \beta_1 x_1 + ... + \beta_p x_p + c$$

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 $\mu \in (0, 1)$ 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 $x_1, \ldots, x_p$ 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 perform variable selection, ease of interpretation supported by visualisations, and the straight- forward incorporation of interaction effects.

An example of tree formation is :

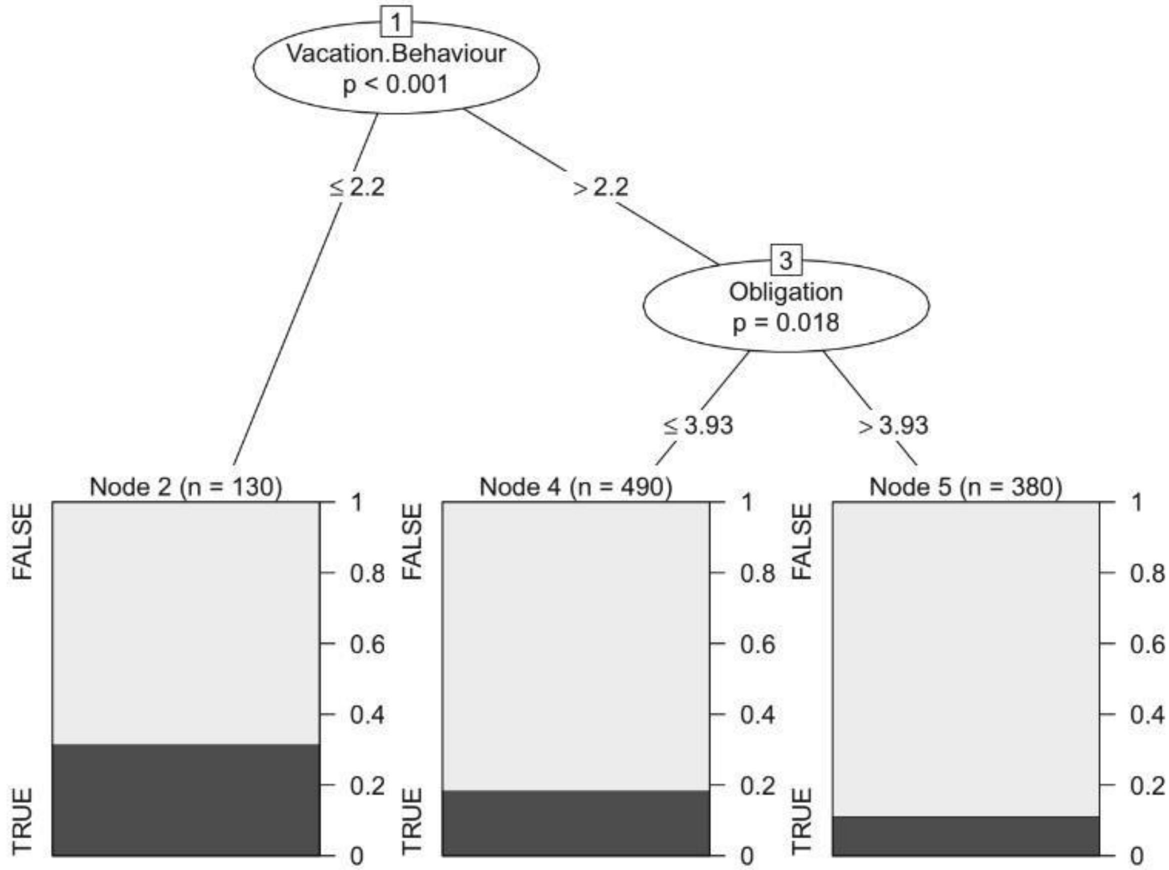


Fig. 9.15 Conditional inference tree using membership in segment 3 as dependent variable for the Australian travel motives data set

The node containing all consumers is the root node. Nodes that are not split further are terminal nodes. When the terminal nodes are reached, regression can be performed to create segments.

Step - 8 Selecting the Target Segment

Market segmentation is a strategic marketing tool. The selection of one or more target segments is a long term decision significantly affecting the future performance of an organization.
In this process one or more of those market segments need to be selected for targeting.

The first task in this process, therefore, is to ensure that all the market segments that are still under consideration to be selected as target markets have well and truly passed the knock-out criteria test. Once this is done, the attractiveness of the remaining segments and the relative organizational competitiveness for these segments needs to be evaluated. In other words, the segmentation team has to ask a number of questions which fall into two broad categories:

1. Which of the market segments would the organization most like to target? Which segment would the organization like to commit to?

2. Which of the organizations offering the same product would each of the segments most like to buy from? How likely is it that our organization would be chosen? How likely is it that each segment would commit to us?

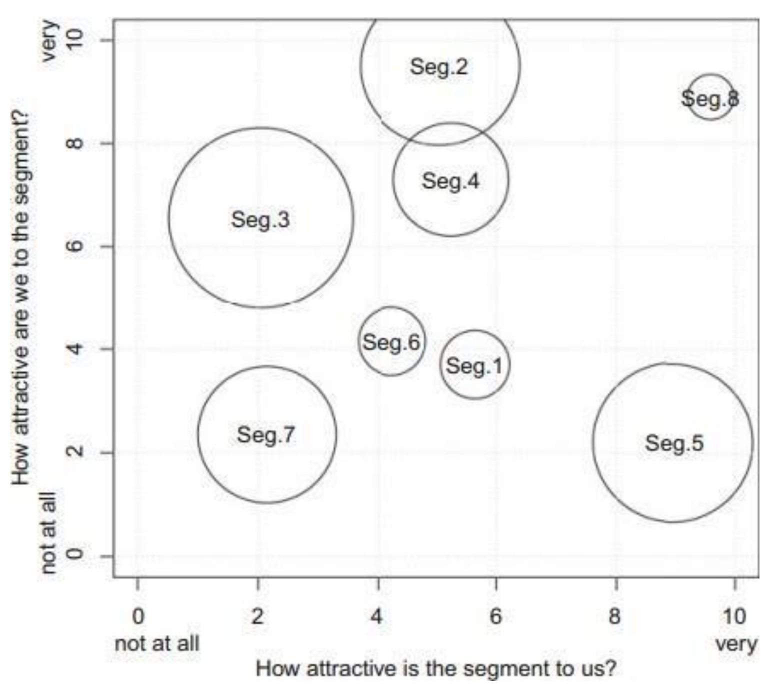
Answering these two questions forms the basis of the target segment decision.

Market Segment Evaluation

The location of each market segment in the segment evaluation plot is then computed by multiplying the weight of the segment attractiveness criterion (agreed upon in Step 2) with the value of the segment attractiveness criterion for each market segment. The value of the segment attractiveness criterion for each market segment is determined by the market segmentation team based on the profiles and descriptions resulting from Steps 6 and 7. The result is a weighted value for each segment attractiveness criteria for each segment. Those values are added up, and represent a segment's overall attractiveness (plotted along the x-axis).

	Weight	Seg 1	Seg 2	Seg 3	Seg 4	Seg 5	Seg 6	Seg 7	Seg 8
How attractive is the segment to us? (segment attractiveness)									
Criterion 1	25%	5	10	1	5	10	3	1	10
Criterion 2	35%	2	1	2	6	9	4	2	10
Criterion 3	20%	10	6	4	4	8	2	1	9
Criterion 4	10%	8	4	2	7	10	8	3	10
Criterion 5	10%	9	6	1	4	7	9	7	8
Total	100%	5.65	5.05	2.05	5.25	8.95	4.25	2.15	9.6
How attractive are we to the segment? (relative organisational competitiveness)									
Criterion 1	25%	2	10	10	10	1	5	2	9
Criterion 2	25%	3	10	4	6	2	4	3	8
Criterion 3	25%	4	10	8	7	3	3	1	10
Criterion 4	15%	9	8	3	9	4	5	3	9
Criterion 5	10%	1	8	6	2	1	4	4	8
Total	100%	3.7	9.5	6.55	7.3	2.2	4.15	2.35	8.9
Size		2.25	5.25	6.00	3.75	5.25	2.25	4.50	1.50

The value of each segment on the axis labelled How attractive are we to the segment? is calculated in the same way as the value for the attractiveness of each segment from the organisational perspective: first, criteria are agreed upon, next they are weighted, then each segment is rated, and finally the values are multiplied and summed up. The data underlying the segment evaluation plot based on the hypothetical example



Step - 9 Customizing the Marketing Mix

Marketing was originally seen as a toolbox to assist in selling products, with marketers mixing the ingredients of the toolbox to achieve the best possible sales results (Dolnicar and Ring 2014). In the early days of marketing, Borden (1964) postulated that marketers have at their disposal 12 ingredients: product planning, packaging, physical handling, distribution channels, pricing, personal selling, branding, display, advertising, promotions, servicing, fact finding and analysis. Many versions of this marketing mix have since been proposed, but most commonly the marketing mix is understood as consisting of the 4Ps: Product, Price, Promotion and Place (McCarthy 1960).

How the target segment decision affects marketing mix development

The above picture 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.

Step - 10 Evaluation and Monitoring

Ongoing Tasks in Market Segmentation

After the segmentation strategy is implemented, two additional tasks need to be performed on an ongoing basis:

1. The effectiveness of the segmentation strategy needs to be evaluated. Much effort goes into conducting the market segmentation analysis, and customizing the marketing mix to best satisfy the target segment’sneeds. These efforts should result in an increase in profit, or an increase in achievement of the organizational mission. If they did not, the market segmentation strategy failed.
2. The market is not static. Consumers change, the environment, and the actions of competitors change. As a consequence, a process of ongoing monitoring of the market segmentation strategy must be devised. This monitoring process can range from a regular review by the segmentation team, to a highly automatized data mining system alerting the organization to any relevant changes to the size or nature of the target segment.

Evaluating the Success of the Segmentation Strategy

The aim of evaluating the effectiveness of the market segmentation strategy is to determine whether developing a customized marketing mix for one or more segments did achieve the expected benefits for the organization.

Segment Evolution

Segments evolve. Like any characteristic of markets, market segments change over time. The environments in which the organization operates, and actions taken by competitors change. Haley (1985),the father of benefit segmentation, says that not following-up a segmentation study means sacrificing a substantial part of the value it is able to generate. Haley (1985) proceeds to recommend a tracking system to ensure that any changes are identified as early as possible and acted upon. Haley refers to the tracking system as an early warning system activating action only if an irregularity is detected. Or, as Cahill (2006) puts it (p. 38): Keep testing, keep researching, keep measuring. People change, trends change, values change, everything changes.

A number of reasons drive genuine change of market segments, including: evolution of consumers in terms of their product savviness or their family life cycle; the availability of new products in the category; and the emergence of disruptive innovations changing a market in its entirety.