MARKET SEGMENTATION ANALYSIS

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Market Segmentation

At its core, market segmentation is the practice of dividing your target market into approachable groups. Market segmentation creates subsets of a market based on demographics, needs, priorities, common interests, and other psychographic or behavioral criteria used to better understand the target audience. By understanding your market segments, you can leverage this targeting in product, sales, and marketing strategies.

Market segments can power your product development cycles by informing how you create product offerings for different segments like men vs. women or high income vs. low income.

The Benefits of Market Segmentation

1. **Stronger marketing messages:** You no longer have to be generic and vague – youcan speak directly to a specific group of people in ways they can relate to, because you understand their characteristics, wants, and needs.
2. **Targeted digital advertising:** Market segmentation helps you understand and define your audience's characteristics, so you can direct your marketing efforts to specific ages, locations, buying habits, interests etc.
3. **Developing effective marketing strategies:** Knowing your target audience givesyou a head start about what methods, tactics, and solutions they will be most responsive to.
4. **Better response rates and lower acquisition costs:** These will result from creating your marketing communications both in ad messaging and advanced targeting on digital platforms like Facebook and Google using your segmentation.
5. **Attracting the right customers:** Market segmentation helps you create targeted,clear, and direct messaging that attracts the people you want to buy from you.
6. **Increasing brand loyalty:** when customers feel understood, uniquely well servedand trusting, they are more likely to stick with your brand.
7. **Differentiating your brand from the competition:** More specific, personal messaging makes your brand stand out.
8. **Identifying niche markets:** segmentation can uncover not only underserved markets, but also new ways of serving existing markets – opportunities which can be used to grow your brand.
9. **Staying on message:** As segmentation is so linear, it's easy to stay on track withyour marketing strategies, and not get distracted into less effective areas.
10. **Driving growth:** You can encourage customers to buy from you again, or trade upfrom a lower-priced product or service.

11. **Enhanced profits:** Different customers have different disposable incomes; pricescan be set according to how much they are willing to spend. Knowing this can ensure you don't over (or under) sell yourself.
12. **Product development:** You'll be able to design with the needs of your customers top of mind, and develop different products that cater to your different customer base areas.

Types of market segmentation

- Demographic Segmentation
- Geographic Segmentation
- Firmographic Segmentation
- Behavioral Segmentation
- Psychographic Segmentation

How to get started with segmentation

1. Define your market
2. Segment your market
3. Understand your market
4. Create your customer segments
5. Test your marketing strategy

Market segmentation strategy

- In times of rapid change
- On a yearly basis
- At periodic times during the year

When updating your market segmentation strategy, consider these three areas:

1. Acknowledge what has changed
2. Don't wait to start planning
3. Go from what to why

Datasets for market segmentation analysis, considered here:

- Risk taking: CSV
- Austrian winter vacation activities:
  - 1997/98, 27 activities: CSV
  - 1991/92, 11 activities: CSV
  - 1997/98, 11 activities: CSV
- Australian vacation activities: CSV (segmentation variables), CSV (descriptor variables)
- Australian travel motives: CSV (complete data set), CSV (segmentation variables), CSV (descriptor variables)
- Fast food: CSV

10 steps in Market segmentation analysis

- **Step 1: Exploring data**
- **Step 2: Extracting segments - Distance-based methods**
- **Step 3: Extracting segments - Model-based methods**
- **Step 4: Extracting segments - Algorithms with integrated variable selection**
- **Step 5: Extracting segments - Data structure analysis**
- **Step 6: Profiling segments**
- **Step 7: Describing segments**
- **Step 8: Selecting the target segments**
- **Step 9: Customizing the marketing mix**
- **Step 10: Evaluation and monitoring**
- **Case study: Fast food data**

Step 1: Exploring data

First look at data Exploratory data analysis and, if necessary, pre-processes the data after it has been collected. This round of investigation also provides recommendations for the best algorithm for extracting useful market segments.

Data exploration, on a more technical level, aids in

(1) identifying the variables' measurement levels.

(2) investigating the univariate distributions of each variable and

(3) assessing dependency patterns between variables.

Furthermore, data may need to be pre-processed and prepared before being utilized as input for various segmentation algorithms. The data exploration stage yields information on the suitabilityof various segmentation approaches for extracting market segments.

- **Data cleaning:**

  Cleaning the data is the first step before beginning data analysis. This involves ensuring that all values have been appropriately recorded and that consistent labels for categorical variable levels have been utilized. The range of feasible values for many metric variables is known ahead of time. For example, one's age (in years) should be between 0 and 110. It's simple to see if the data has any unusual values, which could indicate problems in data gathering or data entry.

- **Pre-processing:**

  1) Categorical variables

  2) Numerical variables

- **Principal component analysis:**

  Principal components analysis (PCA) converts a multivariate data set with metric variables into a new data set with uncorrelated and importance-ordered variables called principal components. The most variability is contained in the first variable (principal component), the second principal component contains the second most variability, and so on. Because principal components analysis generates as many new variables as here were old ones, observations (consumers) retain their relative positions to one another after transformation, and the dimensionality of the new data set remains the same.

Step 2: Extracting segments - Distance-based methods

Distance-based algorithms are machine learning algorithms that classify queries by computing distances between these queries and a number of internally stored exemplars. Exemplars that are closest to the query have the largest influence on the classification assigned to the query. Two specific distance-based algorithms, the nearest neighbor algorithm and the nearest-hyperrectangle algorithm, are studied in detail.

It is shown that the k-nearest neighbor algorithm (kNN) outperforms the first nearest neighbor algorithm only under certain conditions. Data sets must contain moderate amounts of noise. Training examples from the different classes must belong to clusters that allow an increase in the value of k without reaching into clusters of other classes. Methods for choosing the value of k for kNN are investigated. It showed that one-fold cross-validation on a restricted number of values for k suffices for best performance. It is also shown that for best performance the votes of the k-nearest neighbors of a query should be weighted in inverse proportion to their distances from the query.

Principal component analysis is shown to reduce the number of relevant dimensions substantially in several domains. Two methods for learning feature weights for a weighted Euclidean distance metric are proposed. These methods improve the performance of kNN and NN in a variety of domains.

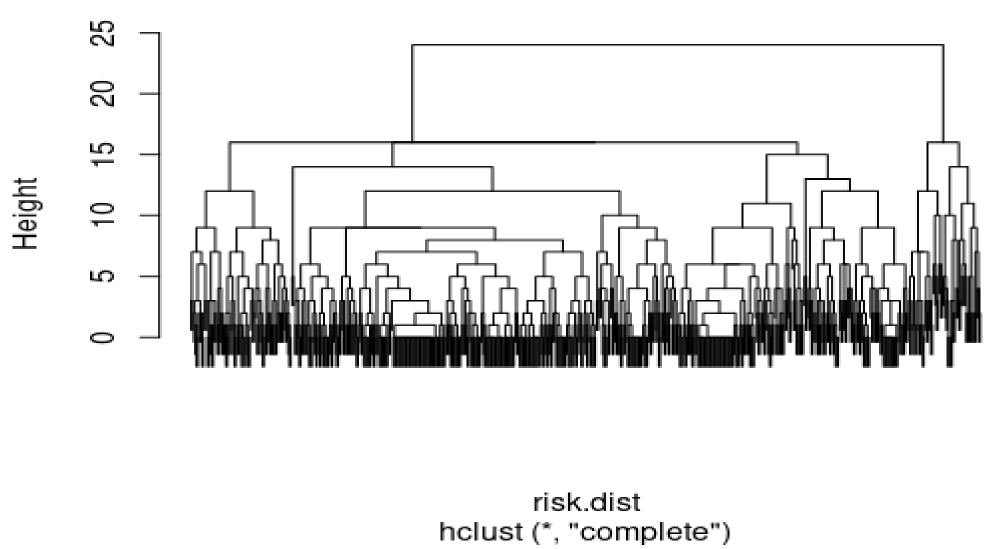
The nearest-hyperrectangle algorithm (NGE) is found to give predictions that are substantially inferior to those given by kNN in a variety of domains. In parts of the input space that can be represented by a single hyperrectangle and kNN otherwise, is introduced.

- **Distance measures:** Distance measures play an important role in machine learning.A distance measure is an objective score that summarizes the relative difference between two objects in a problem domain.
  Most commonly, the two objects are rows of data that describe a subject (such as a person, car, or house), or an event (such as a purchase, a claim, or a diagnosis).

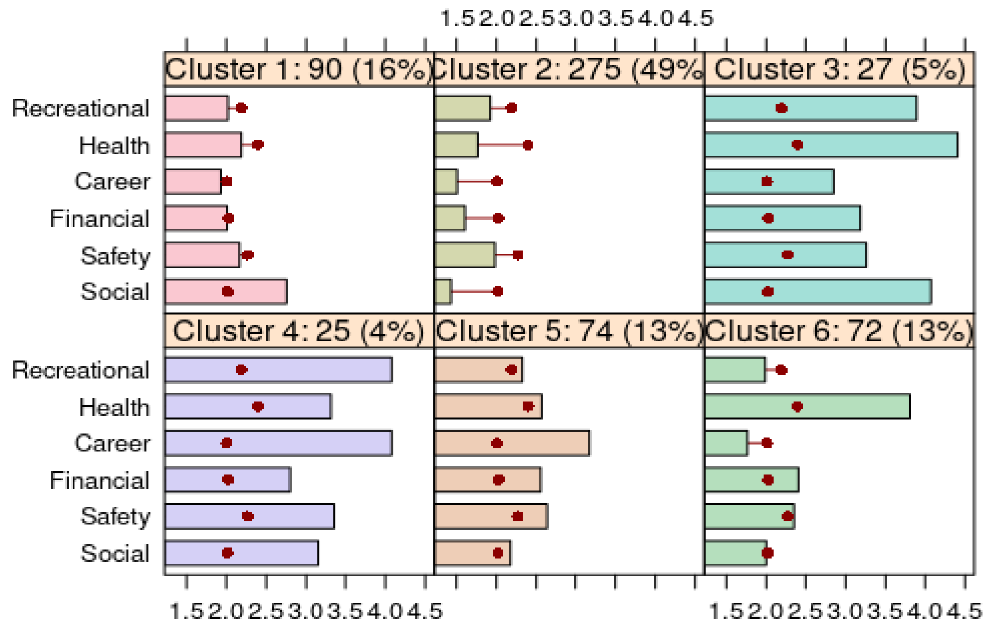
- **K-Means clustering:** K-Means Clustering is an Unsupervised Learning algorithm, which groups the unlabeled dataset into different clusters. Here K defines the number of predefined clusters that need to be created in the process, as if K=2, there will be two clusters, and for K=3, there will be three clusters, and so on.

- **Hierarchical clustering:** Hierarchical clustering is another unsupervised machine learning algorithm, which is used to group the unlabeled datasets into a cluster and also known as hierarchical cluster analysis or HCA. In this algorithm, we develop the hierarchy of clusters in the form of a tree, and this tree-shaped structure is known as the dendrogram.

(Fig.1) Here is the example of Hierarchical clusters of risk dataset.

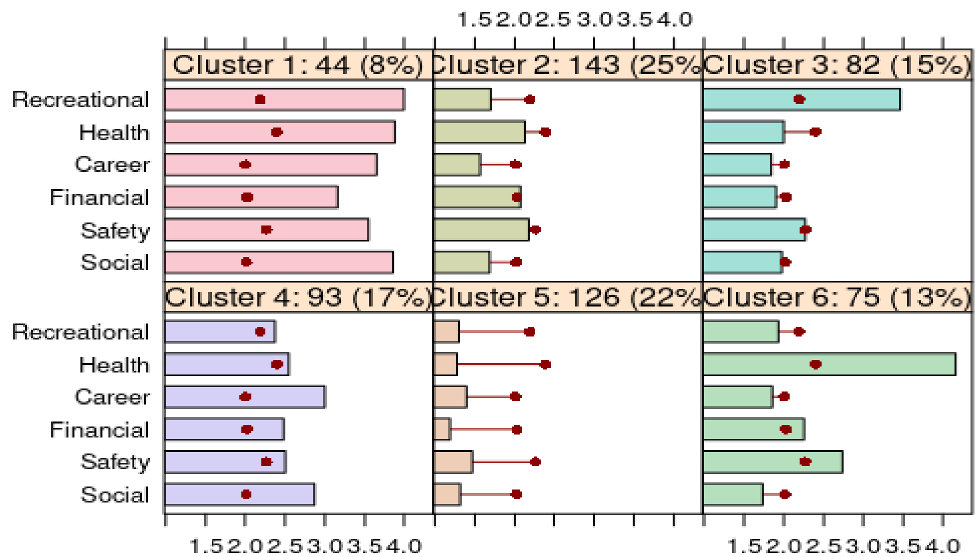


(Fig.2) **Bar chart of Risk dataset with 6 clusters.**

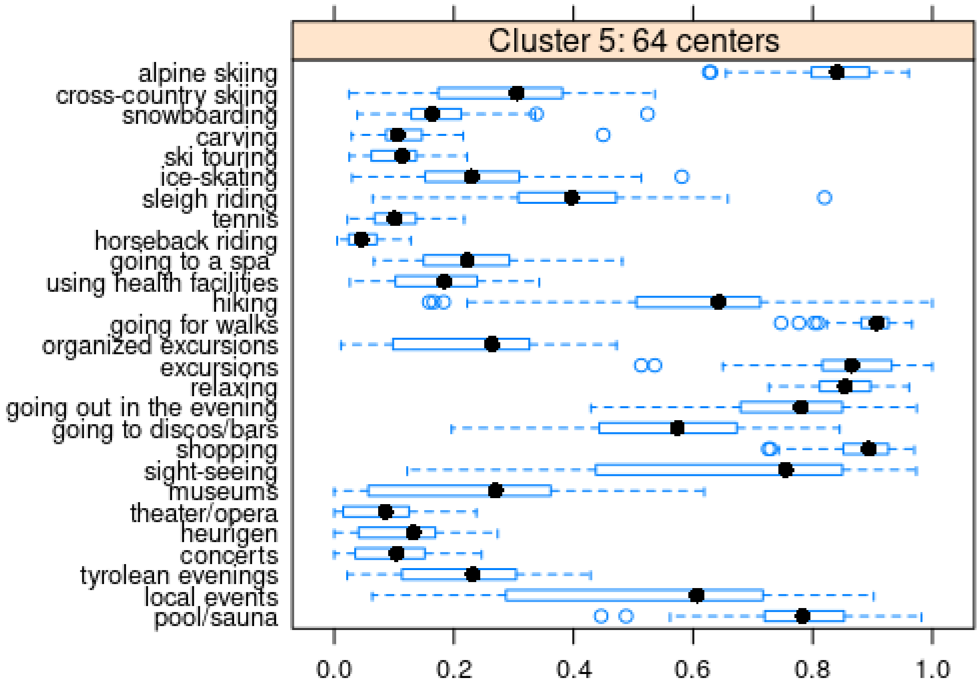


- **Partitioning method:** This clustering method classifies the information into multiple groups based on the characteristics and similarity of the data. It's the data analysts to specify the number of clusters that has to be generated for the clustering methods.

(Fig.3) Example: Bar chart of Partition clusters of tourist risk taking data.



(Fig.4) Bagged clustering of winterActiv data.



Step 3: Model-based method

Model based method have been proposed as an alternative segment extraction technique. As opposed to distance-based clustering methods, model-based segment extraction methods do not use similarities or distances to assess which consumers should be assigned to the same market segment. Instead, they assume that the true market segmentation solution – which is unknown – has the following two general properties:

1. each market segment has a certain size.
2. if a consumer belongs to market segment A, that consumer will have characteristics which are specific to members of market segment A.

These two properties are assumed to hold, but the exact nature of these properties, the sizes of these segments, and the values of the segment-specific characteristics is not known in advance.

Model-based methods can be seen as selecting a general structure, and then fine tuning the structure based on the consumer data. The model-based methods used in this section are called finite mixture models because the number of market segments is finite, and the overall model is a mixture of segment-specific models.

The two properties of the finite mixture model are

Property 1: (that each market segment has a certain size) implies that the segment membership z of a consumer is determined by the multinomial distribution with segment sizes π:

$$\mathbf{z \sim Multinomial(\pi)}$$

Property 2: states that members of each market segment have segment-specific characteristics. These segment-specific characteristics are captured by the vector θ, containing one value for each segment-specific characteristic. Function f (), together with θ, captures how likely specific values y are to be observed in the empirical data, given that the consumer has segment membership z, and potentially given some additional pieces of information x for that consumer:

$$\mathbf{f\,(y|x,\theta z)}$$

As in the case of clustering methods, the number of segments k to be extracted should be mentioned in advance. Information criteria are used to select no of market segments. Most common are Akaike information criterion or AIC, the Bayesian information criterion or BIC and the integrated completed likelihood or ICL. All these criteria use the likelihood as a measure ofgoodness-of-fit of the model to the data and penalize for the number of parameters estimated. This penalization is necessary because the maximum likelihood value increases as the model becomes more complex (more segments, more independent variables). Comparing models of different complexity using maximum likelihoods will therefore always lead to the recommendation of the larger model. The criteria differ in the exact value of the penalty. The specific formulae for AIC, BIC and ICL are given by:

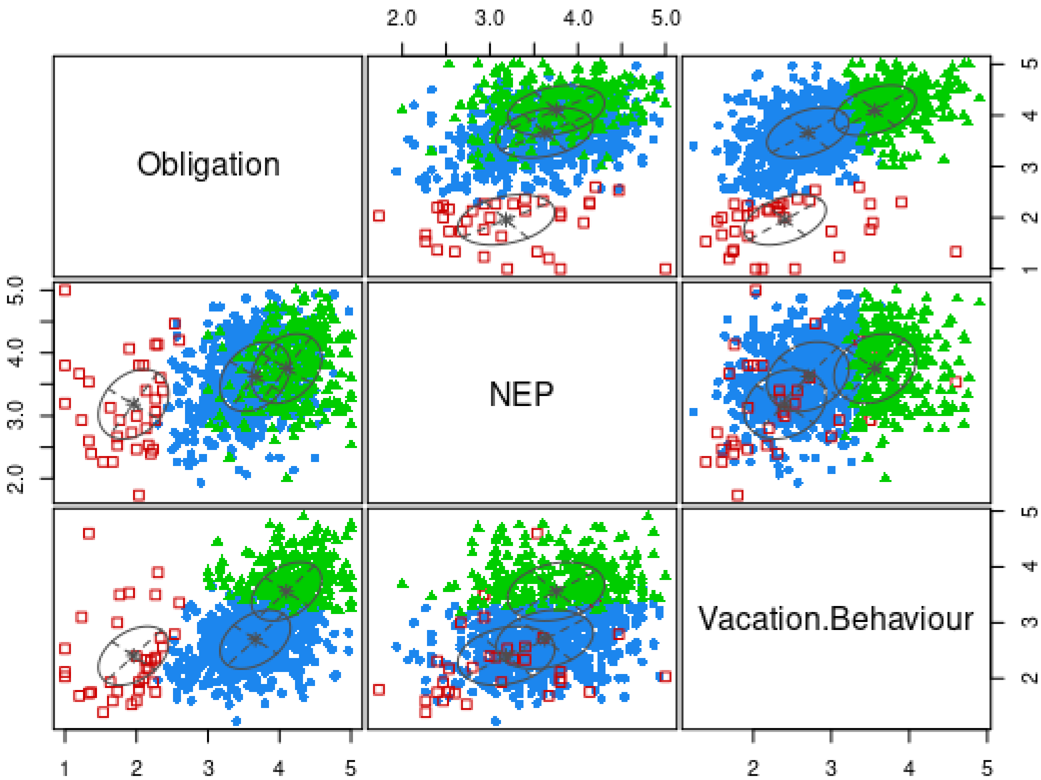
$$\mathbf{AIC = 2df - 2\log(L)}$$

$$\mathbf{BIC = \log(n)df - 2\log(L)}$$

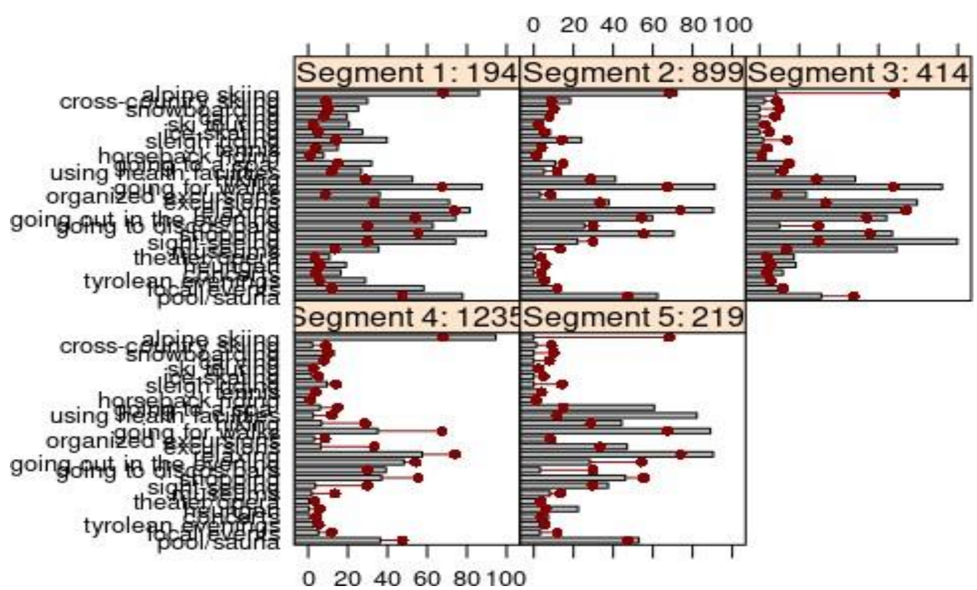
$$\mathbf{ICL = \log(n)df - 2\log(L) + 2ent}$$

- **Mixtures distribution:** A mixture distribution is the probability distribution of a random variable that is derived from a collection of other random variables as follows: first, a random variable is selected by chance from the collection according to given probabilities of selection, and then the value of the selected random variable is realized. The underlying random variables may be random real numbers, or they may be random vectors (each having the same dimension), in which case the mixture distribution is a multivariate distribution.

(Fig.5) **Example: Mixture distribution of Australian motives data on vacation behavior**



(Fig.6) Bar chart of winterActiv data with clusters size as 5



- **Mixtures of regression:** Mixtures models are an exploratory approach that searchfor evidence of heterogeneity in the effects of a predictor on an outcome. Finite mixture of regression models assumes 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. To assess to which market segments the mixture model assigns observations to, observations are plotted in a scatter plot coloring them by segment membership. Finite mixture models are more complicated than distance-based methods. The additional complexity makes finite mixture models very flexible. It allows using any statistical model to describe a market segment. Consequently, finite mixture models can accommodate a wide range of different data characteristics.

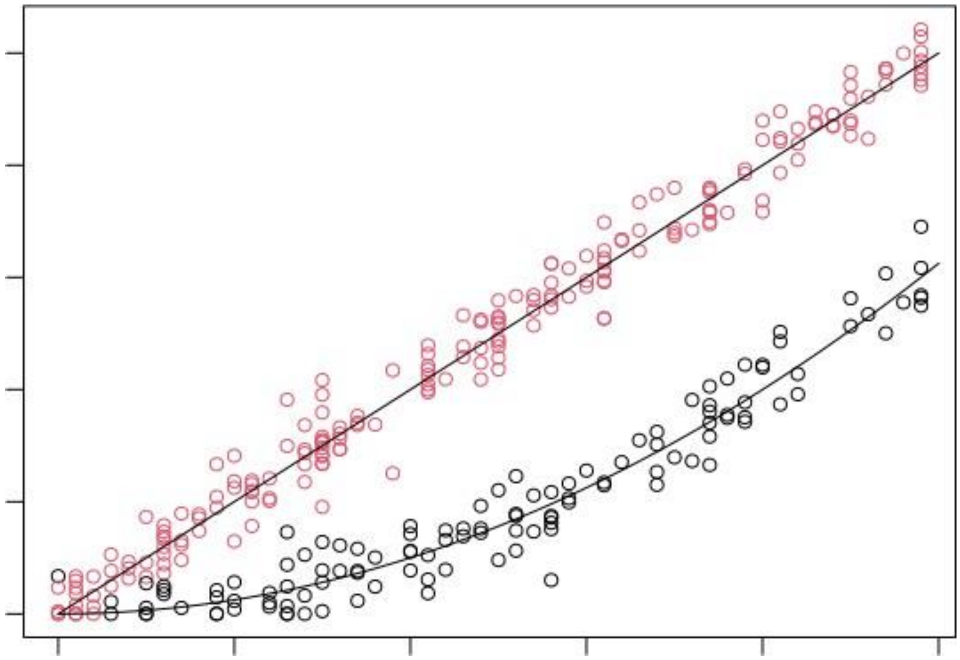
(Fig.7) Fitting regression with theme park dataset.

```
R 4.1.2 · /cloud/project/
> parameters(park.f1)
                      Comp.1       Comp.2
coef.(Intercept)  1.60922212 0.3172187330
coef.rides       -0.11509873 0.9905142322
coef.I(rides^2)   0.01439448 0.0001851452
sigma             2.06269059 1.9898849543
> summary(refit(park.f1))
$Comp.1
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  1.6092221  0.6614741  2.4328  0.01498 *
rides       -0.1150987  0.0563463 -2.0427  0.04108 *
I(rides^2)   0.0143944  0.0010734 13.4101  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

$Comp.2
              Estimate Std. Error z value Pr(>|z|)
(Intercept) 0.31721873 0.48268677  0.6572   0.5111
rides       0.99051423 0.04256194 23.2723   <2e-16 ***
I(rides^2)  0.00018511 0.00080704  0.2294   0.8186
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>
```

(Fig.8) Plotting regression output of theme park.



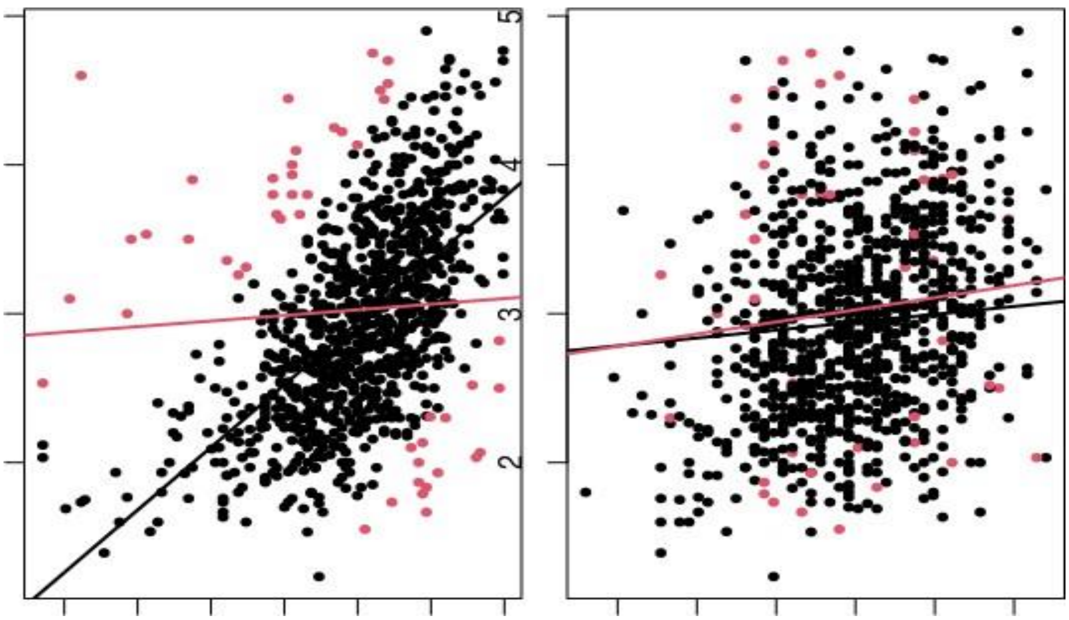
(Fig.9) Fitting regression with Australian motive dataset.

```
R 4.1.2 · /cloud/project/
> summary(refit(envir.m2))
$Comp.1
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 2.944634   0.032669 90.1342  < 2e-16 ***
Obligation  0.418934   0.030217 13.8641  < 2e-16 ***
NEP         0.053489   0.027023  1.9794  0.04778 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

$Comp.2
            Estimate Std. Error z value Pr(>|z|)
(Intercept) 3.023214   0.139161 21.7246   <2e-16 ***
Obligation  0.018619   0.145845  0.1277   0.8984
NEP         0.082207   0.105744  0.7774   0.4369
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

>
```

(Fig.10) Plotting regression output of Australian motive dataset.



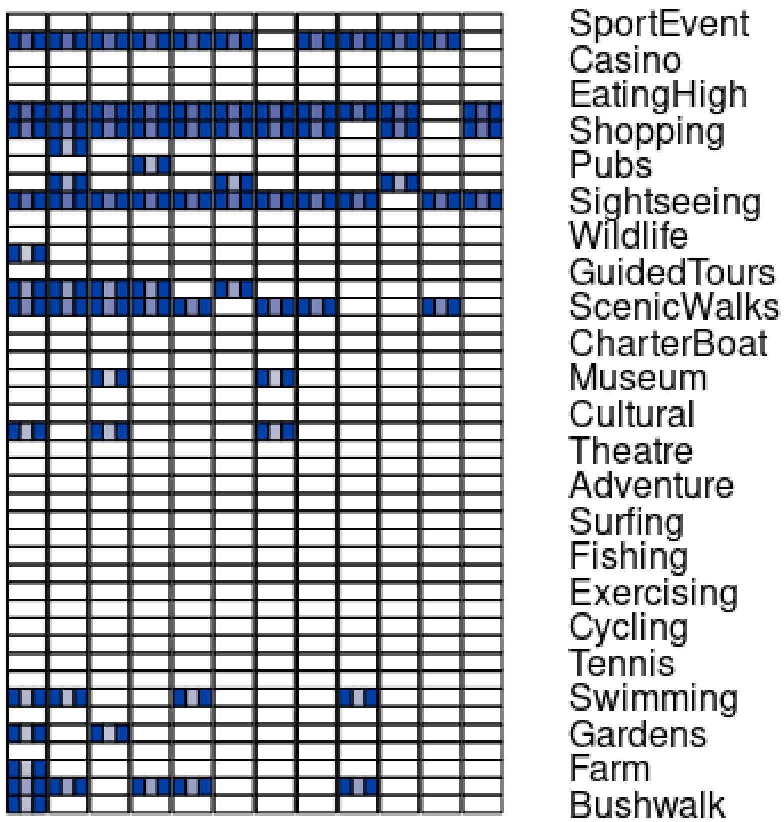
Step 4: Algorithms with integrated variable selection

- **Machine learning algorithms:** Machine learning algorithms can be applied on IoTto reap the rewards of cost savings, improved time, and performance. In the recent era we all have experienced the benefits of machine learning techniques from streaming movie services that recommend titles to watch based on viewing habits to monitor fraudulent activity based on spending patterns of the customers. It can handle large and complex data to draw interesting patterns or trends in them such as anomalies. Machines are needed to process information fast and make decisions when it reaches the threshold. There are many machine learning algorithms listed in Table 1 that help todo better data analysis in industrial IOT devices.

ALGORITHM	TYPE OF TASK
K-nearest neighbor	Classification
Naïve Bayes	Classification
Support vector machine	Classification
Linear regression	Classification/Regression
Random forest	Classification/Regression
K-means	Clustering
Principal component analysis	Feature extraction and dimensionality reduction
Canonical correlation analysis	Feature extraction
Neural networks	Classification/Regression

- **Bi-clustering algorithm:** Simultaneously cluster rows and columns of a data matrix. These clusters of rows and columns are known as biclusters. Each determines a submatrix of the original data matrix with some desired properties.

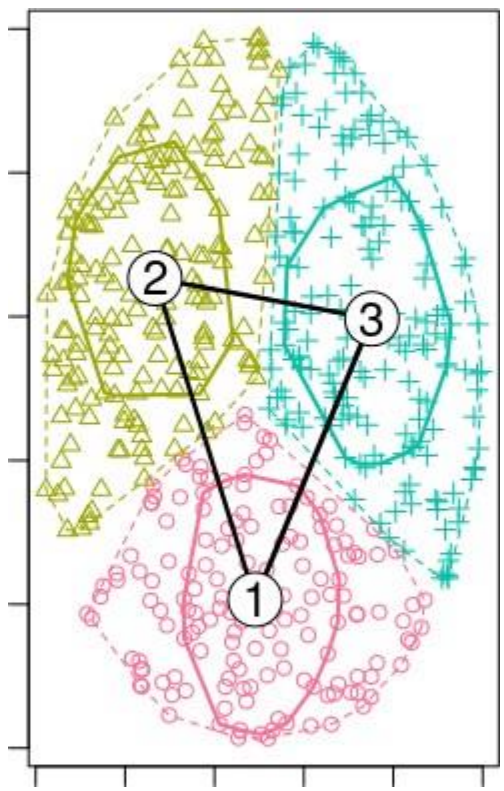
(Fig.11) Example: ausActiv dataset with variable selection,



Step 5: Data structure analysis

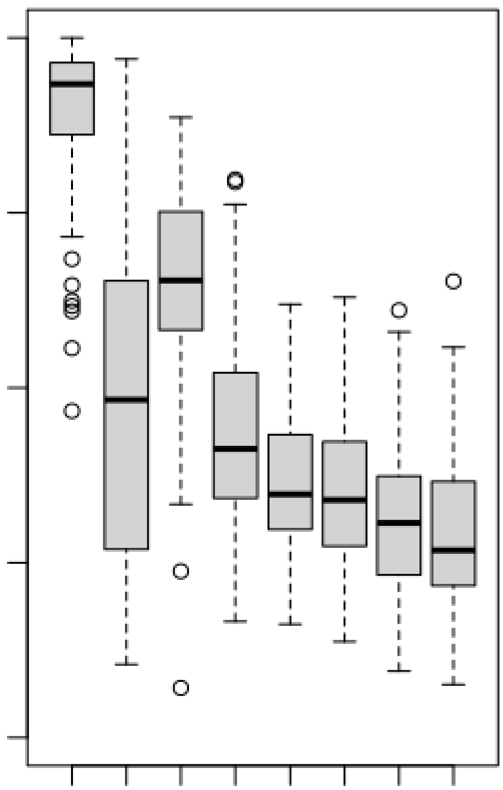
Data Structure Analysis summarizes a program's memory composition and connectivitypatterns by building a Data Structure Graph (DS graph) for each available function in theprogram. Many design features of DS graphs have been carefully chosen to make the analysis very efficient in practice.

(Fig.12) Gorge plots of 3 cluster - ellipse and circles of price feature is shown here.



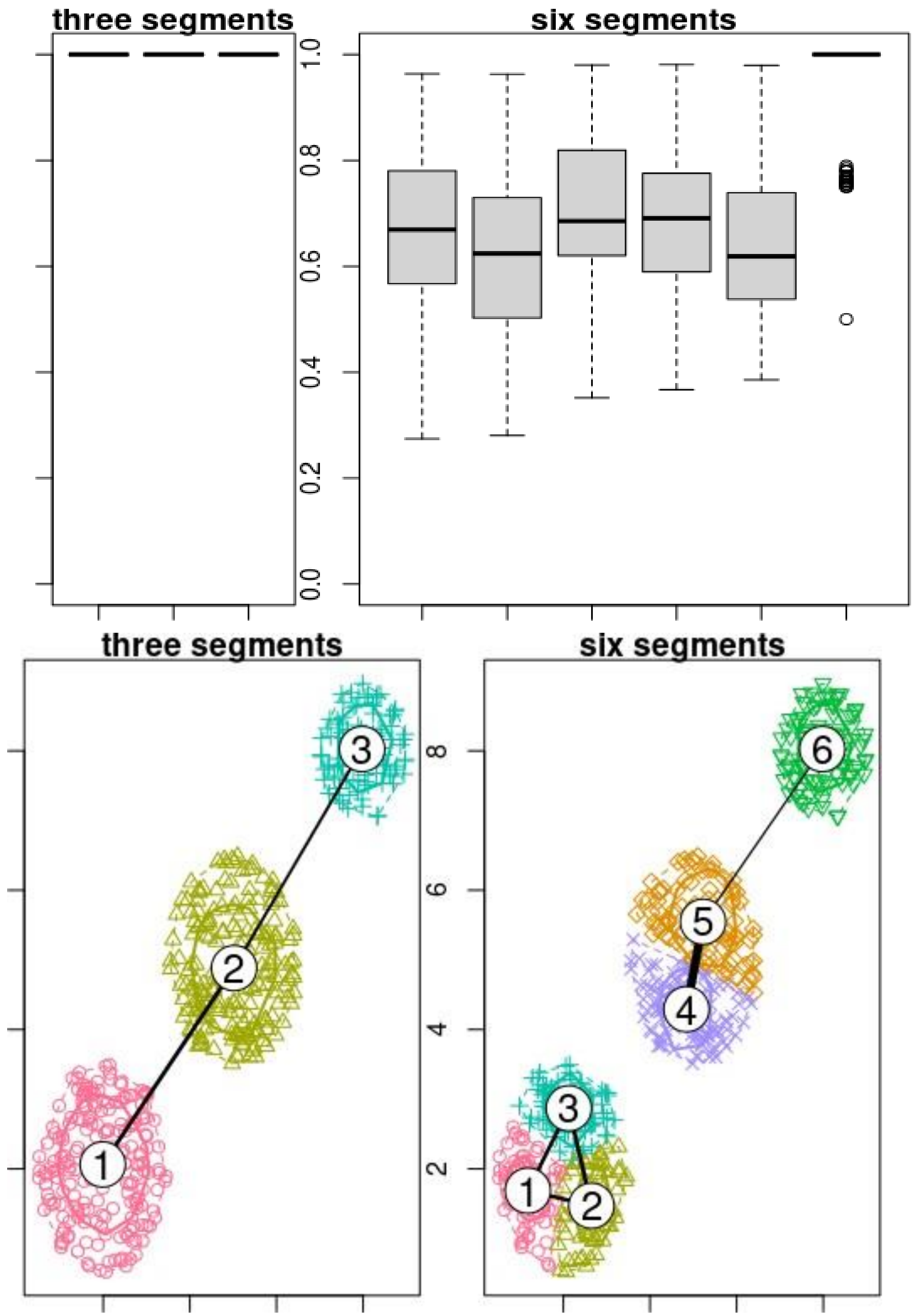
- **Global stability analysis:** Global stability means that the attracting basin of trajectories of a dynamical system is either the state space or a certain region in the state space, which is the defining region of the state variables of the system. Global stability belongs to a kind of asymptotic stability.

(Fig.13) Example: Global stability bar plot of Tourist risk taking data.



- **Segmentation analysis:** It's about dividing broad target markets into subsets of consumers with similar wants and needs. Segmentation analysis helps a company to understand its customers' demographics and their motivations for buying particular products.

(Fig.14) Segment level stability of price feature within solution.



Step 6: Profiling segments

- **Traditional approaches to profiling market segments**

- The purpose of the profiling step is to learn about the market segments that were discovered during the extraction process. Only when data-driven market segmentation is used does profiling become necessary. The profiles of the segments are predefined in common sense segmentation. If, for example, age is employed as a segmentation variable in common sense segmentation, the resulting segments will undoubtedly be age groups. As a result, while using common sense segmentation, Step 6 is not required.

- We use the Australian vacation motives data set. Segments were extracted from this data set in Sect. using the neural gas clustering algorithm with the number of segmentsvaried from 3 to 8 and with 20 random restarts.

(Fig.15) Six segments computed with the neural gas algorithm for the Australian travel motives data set. All numbers are percentages of peoplein the segment or in the total sample agreeing to the motives.

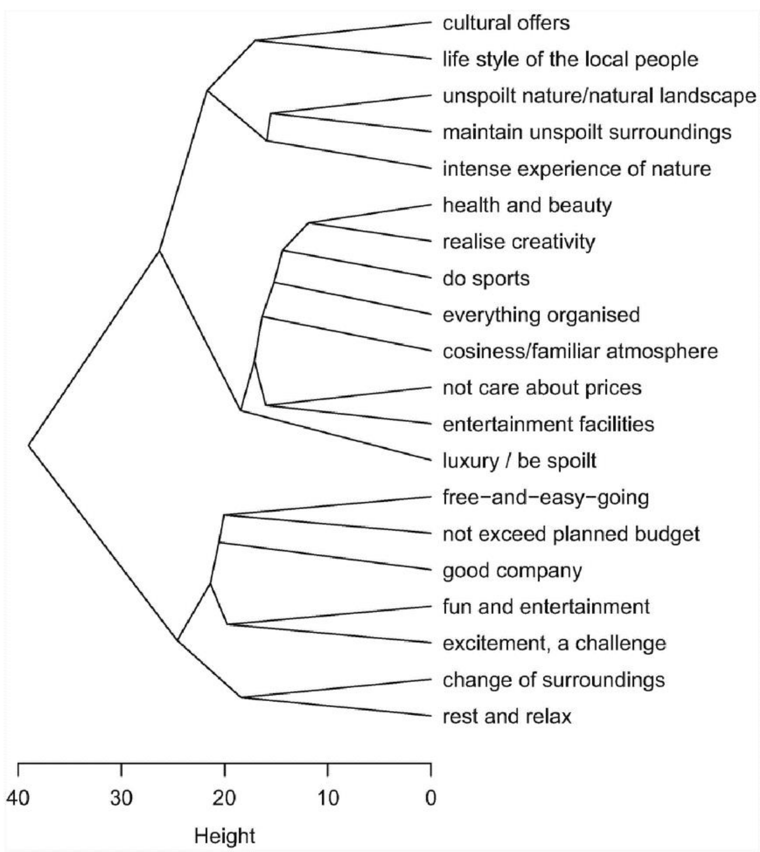
```
> print(cbind(t(clMeans), Total = colMeans(vacmot)) * 100, digits = 0)
                                Seg.1 Seg.2 Seg.3 Seg.4 Seg.5 Seg.6 Total
rest and relax                     85    96    90    79    98    95    90
luxury / be spoilt                 21    23    43    10    92     5    28
do sports                           8    13    11     9    46     9    14
excitement, a challenge             9    16    42    55    77    36    33
not exceed planned budget          20    99     2    52    82    71    51
realise creativity                  2     3     3     8    30    14     8
fun and entertainment               6    71    89    58    94    39    53
good company                       17    55    36    61    77    53    46
health and beauty                   5     7    10     7    48    18    12
free-and-easy-going                14    65    58    42    84    73    52
entertainment facilities            5    25    32    14    55     6    19
not care about prices               9     6    46    16    29    12    18
life style of the local people      9    27    33    90    77    78    46
intense experience of nature        6     8     9    20    51    57    22
cosiness/familiar atmosphere       11    22    12     8    49    27    19
maintain unspoilt surroundings      8    10    16     7    67    95    30
everything organised                7    22    15    13    46    11    16
unspoilt nature/natural landscape   9    11    13    14    69    63    26
cultural offers                     3     3     8    95    63    37    28
change of surroundings             31    81    72    82    88    76    67
```

- **Segment profiling with visualizations**

- Visualizations are useful in the data-driven market segmentation process to inspect, for each segmentation solution, one or more segments in detail. Statistical graphs facilitate the interpretation of segment profiles. They also make it easier to assess the usefulness of a market segmentation solution. The process of segmenting data always leads to a large number of alternative solutions. Selecting one of the possible solutions is a critical decision. Visualizations of solutions assist the data analyst and user with this task.

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

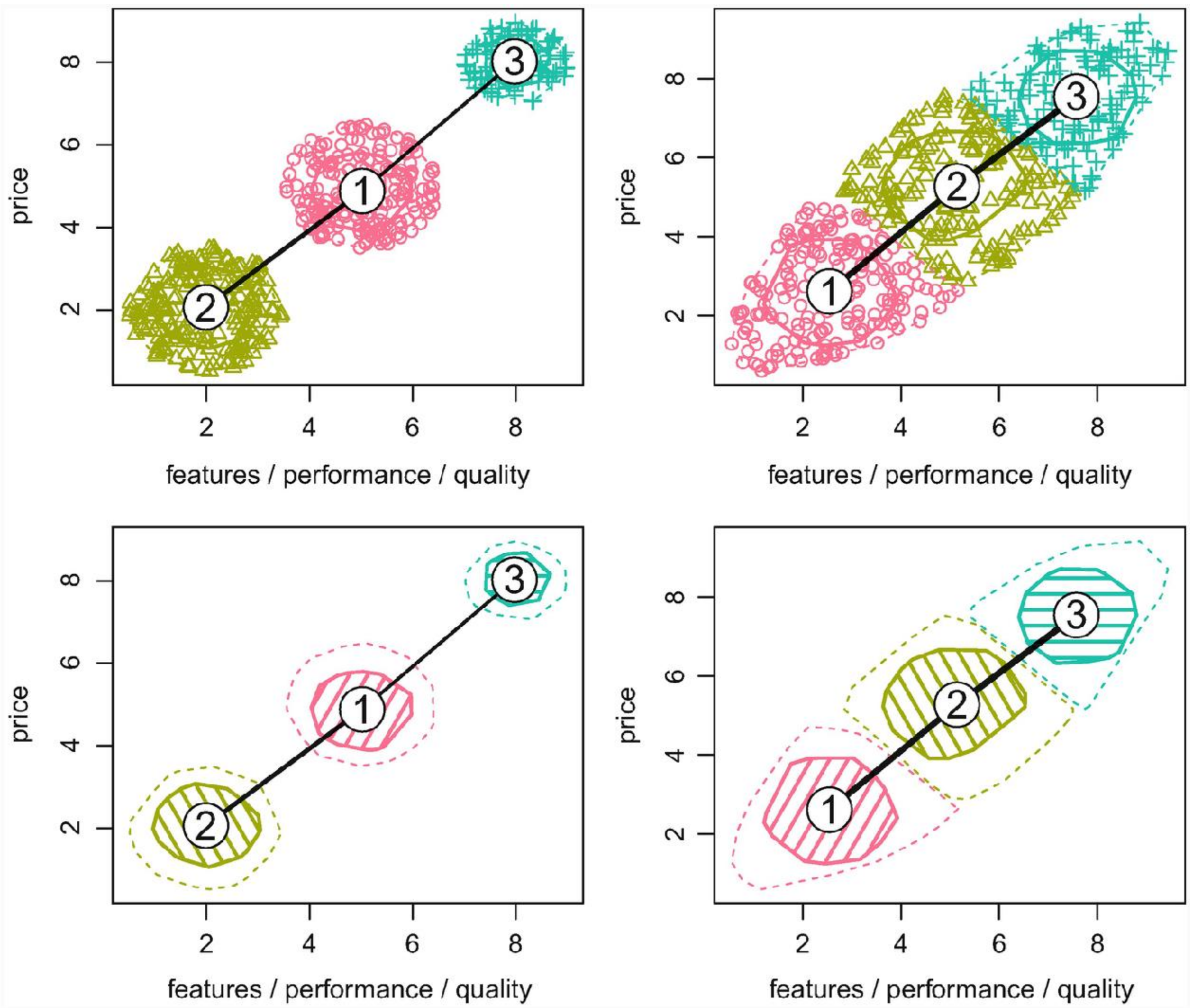
(Fig.16) Hierarchical clustering of the segmentation variables of the Australiantravel motives data set using Ward's method.



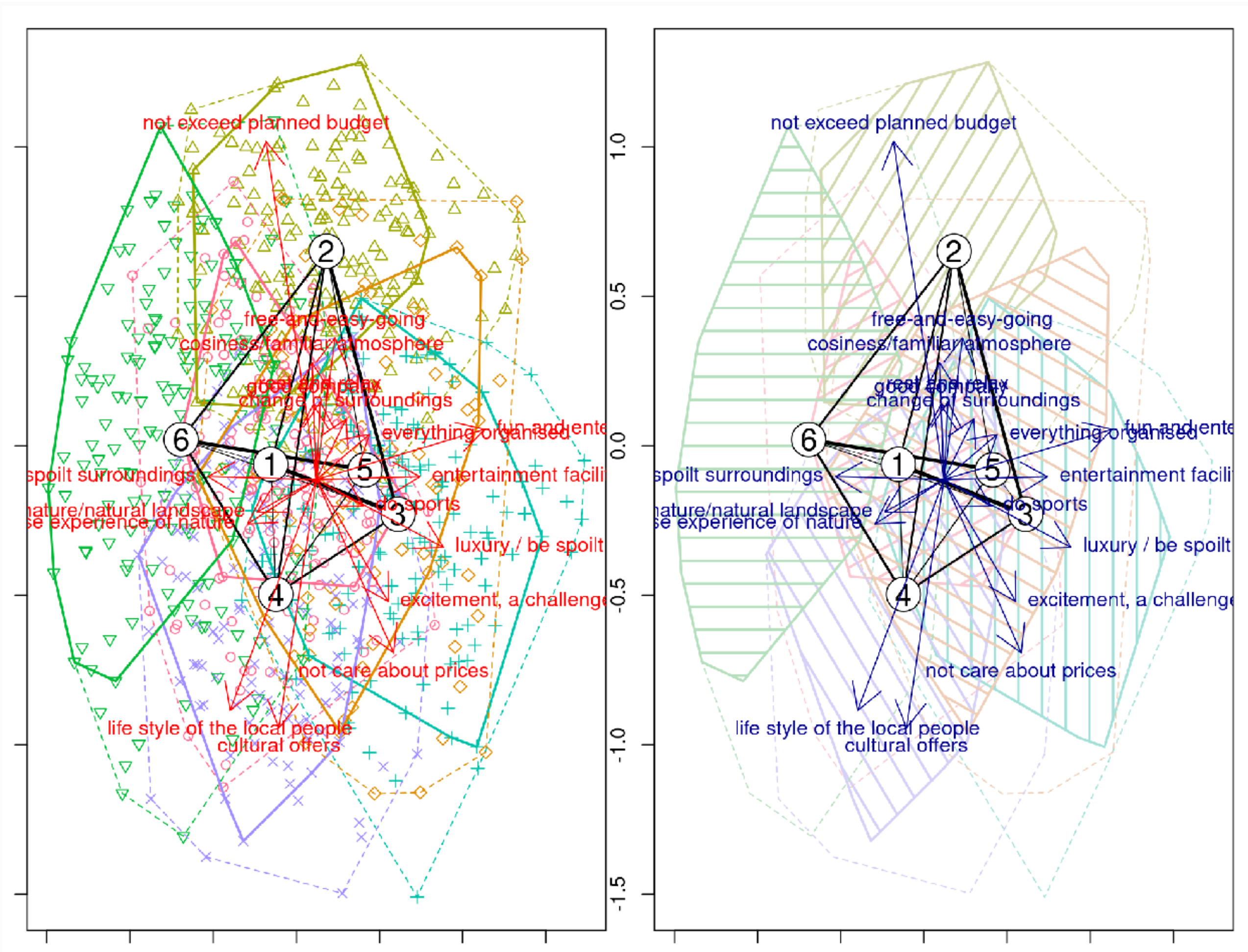
- **Assessing segment separation**

- Segment separation plots are very simple if the number of segmentation variables is low but become complex as the number of segmentation variables increases. But even in such complex situations, segment separation plots offer data analysts and users a quickoverview of the data situation, and the segmentation solution.

(Fig.17) 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).



(Fig.18) Segment separation plot using principal components 2 and 3 for the Australian travel motives data set,



Step 7: Describing segments

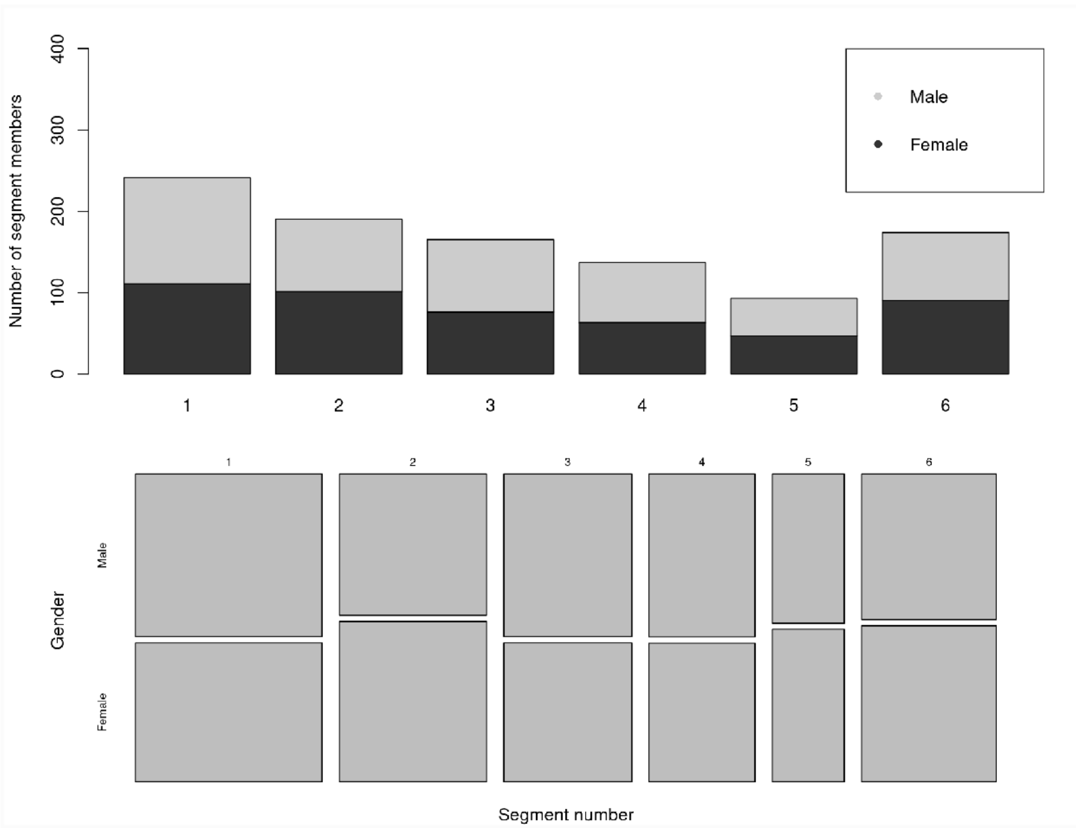
Descriptions of market segments are critical primarily to gain detail insight into the nature of segments and essential for developmental of a customized marketing mix.

We can study differences between market segments in two ways

1) Descriptive statistics – using visualization
2) Inferential statistics

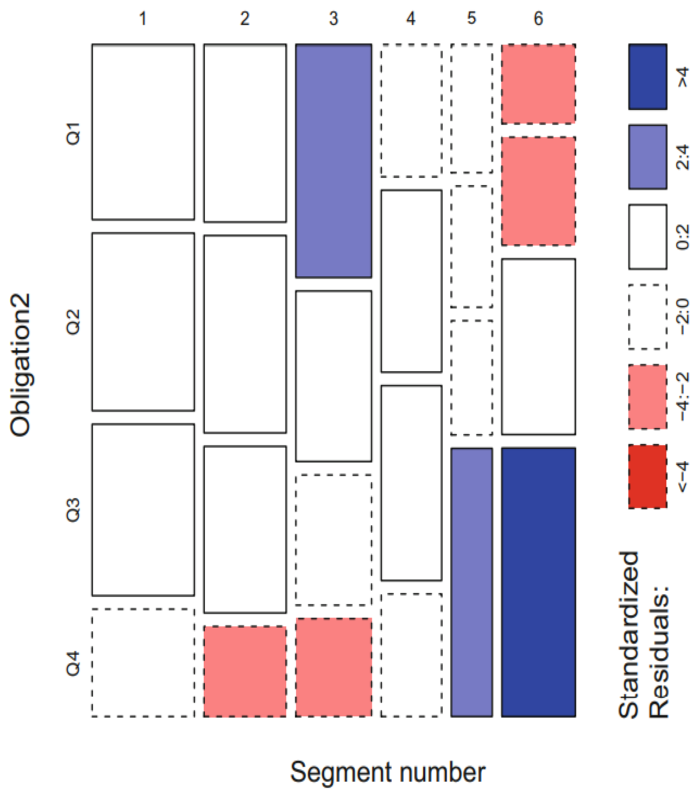
A visual inspection of this cross tabulation is done using a stacked bar chart. Since absolute size of market segment was not inferential from stacked bar plot, mosaic plot is used for acquiring more insight. The mosaic plot provides a deeper insight of segments.

(Fig.19) Cross-tabulation of segment membership and gender for the Australian travel motives dataset.



The mosaic plot can visualize more than two descriptor variables and integrate elements of inferential statistics. Standardized differences that are equivalent to the standardized Pearson residuals are used to describe the positive and negative difference mean in theplot.

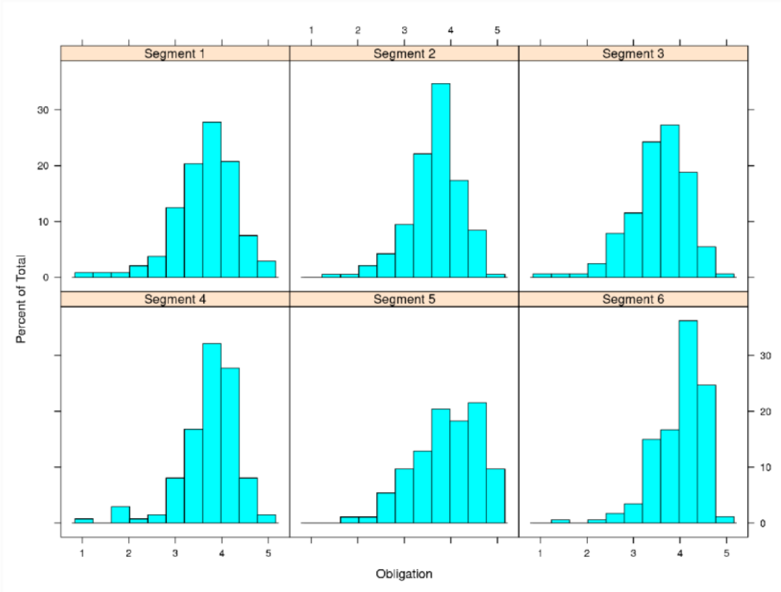
(Fig.20) Visualizing nominal and ordinal descriptor variables.



A single nominal/ ordinal descriptor cross tabulation method is employed. The easiest wayto generate cross tabulation is to add the segment membership (1 to 6 segments) to the descriptor variable (gender) as in the Australian motives dataset is used here for display. Shown in figure 22.

SLS plot is used to trace the value of a metric descriptor variable over a series of market segmentation solutions. The nodes of the SLS plot indicate each segment's mean moralobligation to protect the environment using colors. A deep red color indicates high moralobligation. A light gray color indicates low moral obligation. Light gray edges indicate lowstability values and dark blue edges indicate high stability values

(Fig.21) Visualizing metric descriptor variables.



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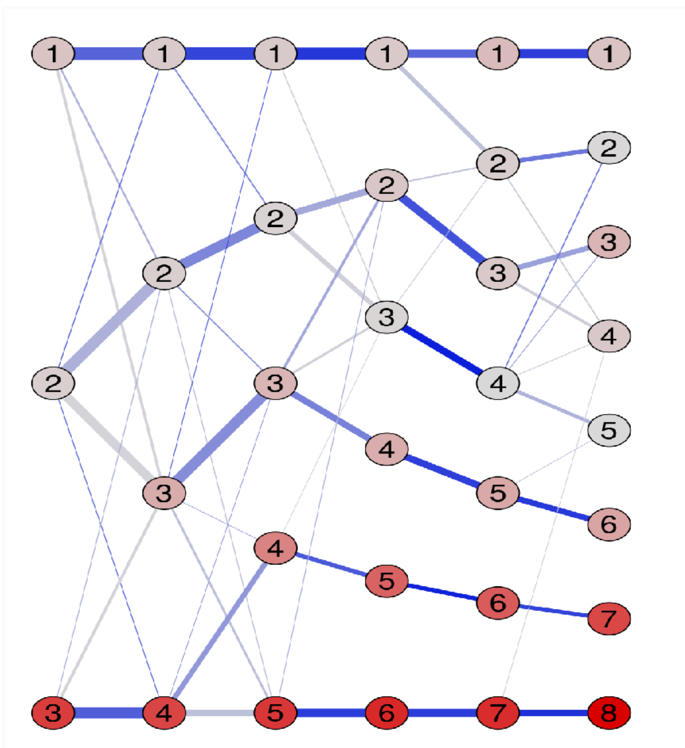
(Fig.22) Segment level stability across solution plot.



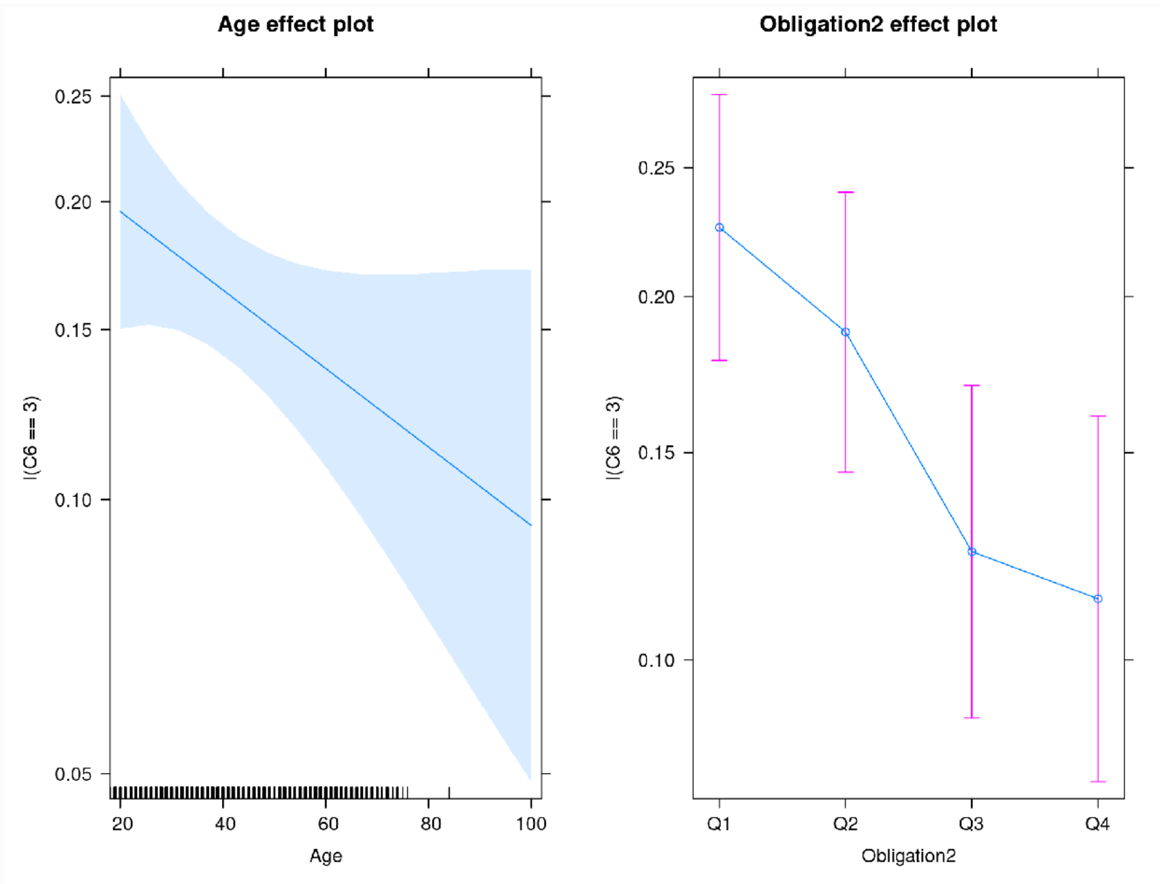
(Fig.23) Binary logistic regression

```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-0.8080  -0.6642  -0.5337  -0.4613   2.3559

Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.759548   0.287806  -2.639  0.00831 **
Age           -0.010691   0.006018  -1.777  0.07565 .
Obligation2Q2 -0.233443   0.218827  -1.067  0.28607
Obligation2Q3 -0.723519   0.241781  -2.992  0.00277 **
Obligation2Q4 -0.828765   0.257747  -3.215  0.00130 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 895.74  on 999  degrees of freedom
Residual deviance: 875.62  on 995  degrees of freedom
AIC: 885.62

Number of Fisher Scoring iterations: 4
```

The below figure shows how the predicted probability of being in segment 3 changes with age (on the left), and with moral obligation categories (on the right). The plot on the left inFig. shows that, for a 20-year-old tourist with an average moral obligation score, the predicted probability to be in segment 3 is about 20%. This probability decreases with increasing age. For 100-year-old tourists the predicted probability to be in segment 3 is only slightly higher than 10%. y. The fact that we can place into the plot a horizontal line lying completely within the gray shaded area, indicates that differences in AGE do not significantly affect the probability to be in segment 3.

The plot on the right side of the figure shows that the probability of being a member of segment 3 decreases with increasing moral obligation. Respondents of average age with a moral obligation value of Q1 have a predicted probability of about 25% to be in segment 3.If these tourists of average age have the highest moral obligation value of Q4, they have apredicted probability of 12%. The 95% confidence intervals of the estimated effects indicate that – despite high uncertainty – probabilities do not overlap for the two most extreme values of moral obligation. This means that including moral obligation in the logistic regression model significantly improves model fit.

(Fig.24) Plot model

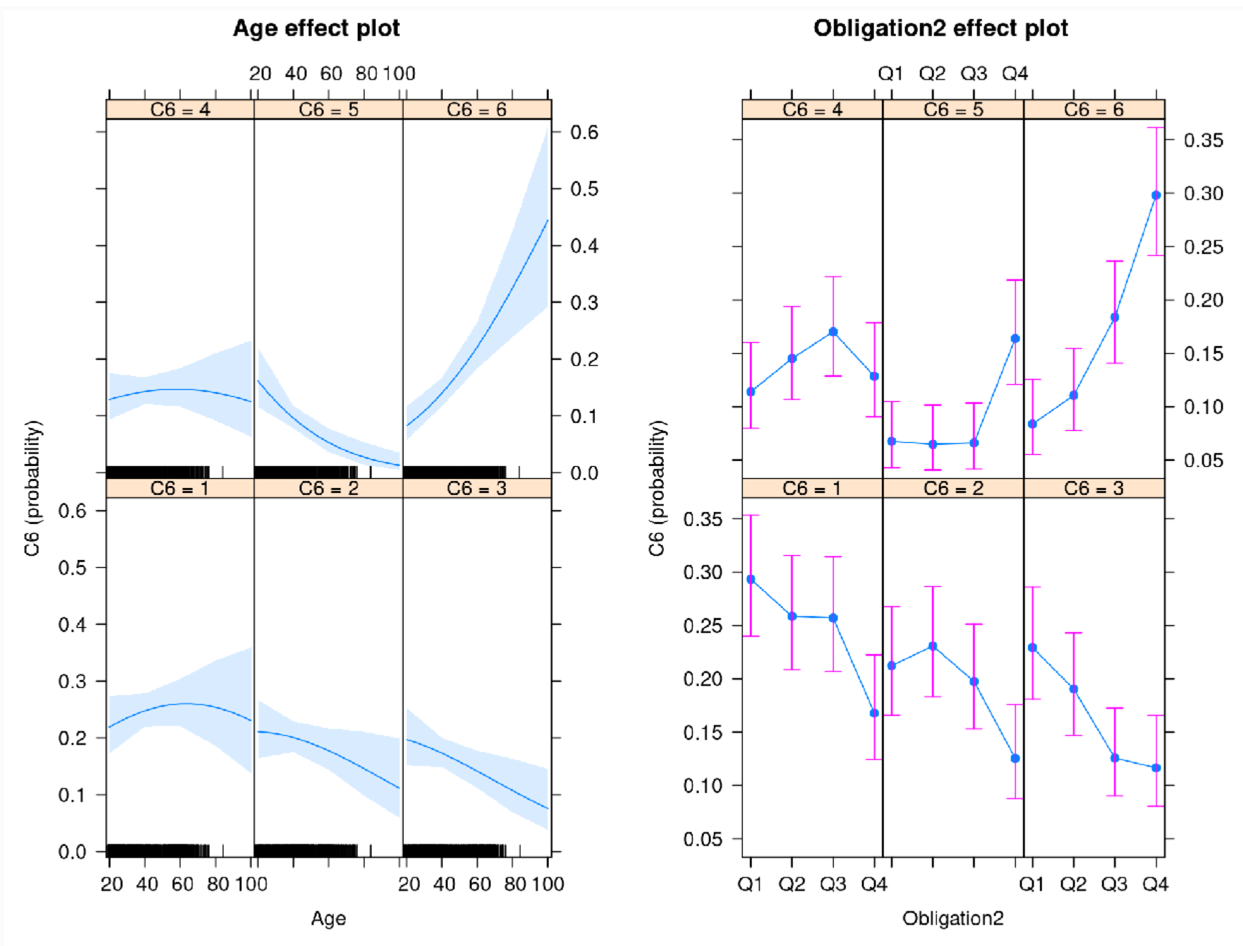


Multinomial logistic regression can fit a model that predicts each segment simultaneously. Because segment extraction typically results in more than two market segments, the dependent variable y is not binary. Rather, it is categorical and assumed to follow a multinomial distribution with the logistic function as link function.

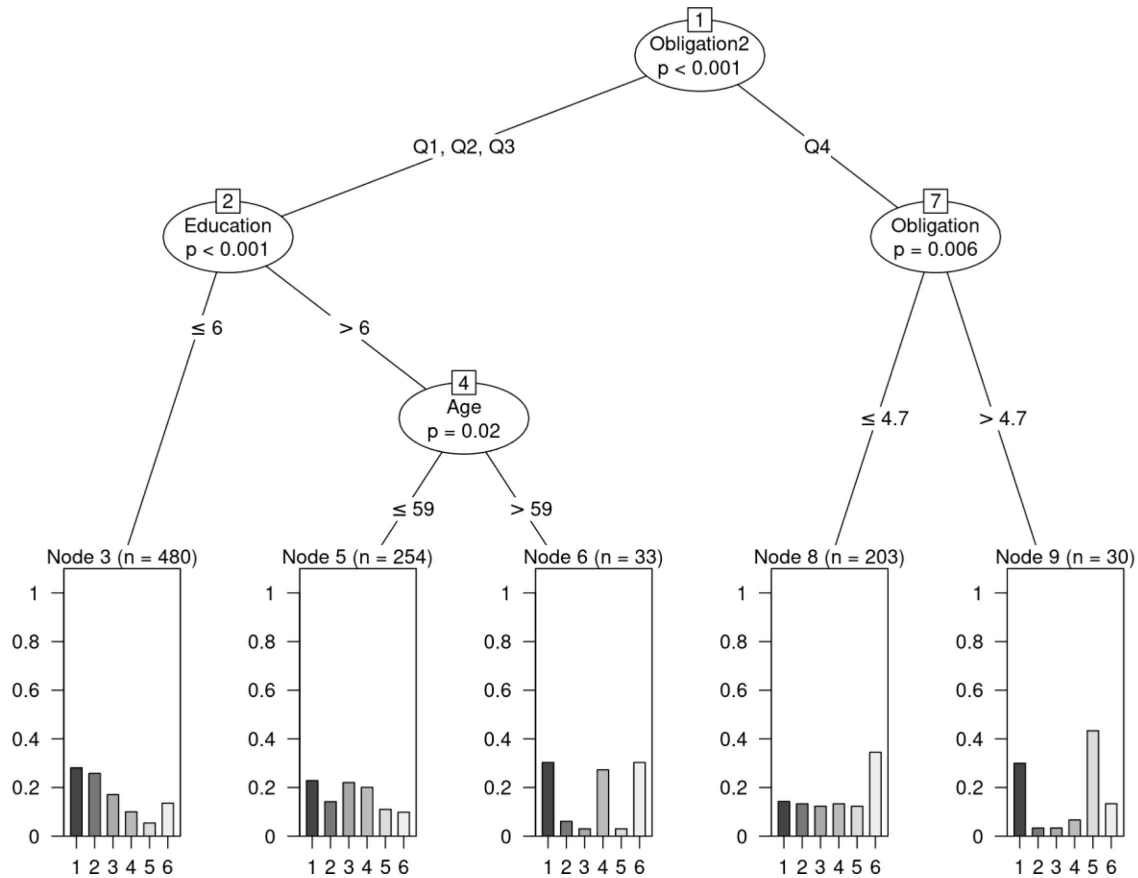
The regression coefficients are arranged in matrix form. Each row contains the regression coefficients for one category of the dependent variable. Each column contains the regression coefficients for one effect of an independent variable.

The regression coefficients and standard errors are obtained from summary.

(Fig.25) Multinomial logistic regression plot,



(Fig.26) Tree based method plot,



Step 8: Selecting the target segments

To select a target market, it is essential for the organizations to study the following factors:

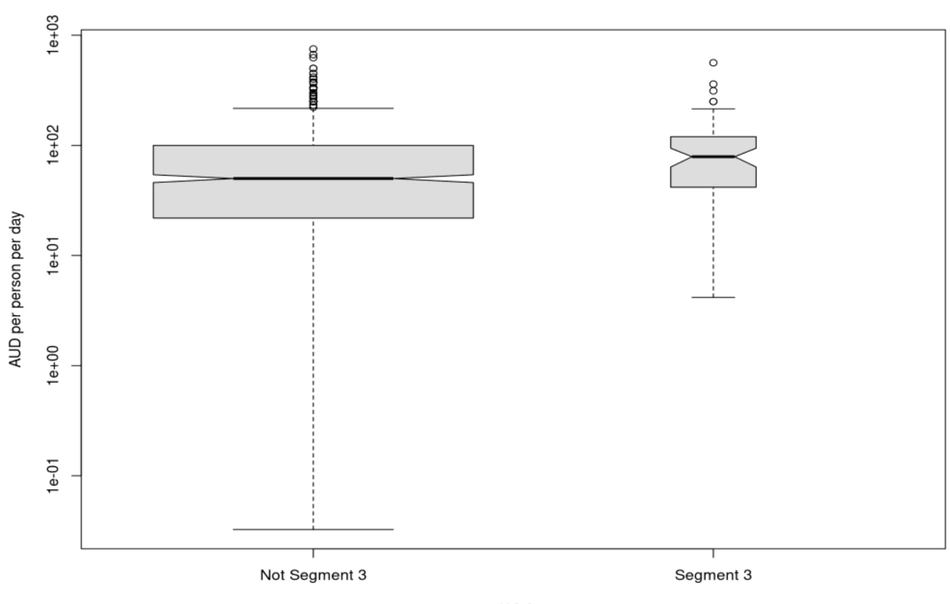
- Understand the lifestyle of the consumers
- Age group of the individuals
- Income of the consumers
- Spending capacity of the consumers
- Education and Profession of the people
- Gender
- Mentality and thought process of the consumers
- Social Status
- Kind of environment individual

In the concentration strategy, a company chooses to focus its marketing efforts on only one market segment. Only one marketing mix is developed: the combination of product offerings, promotional communications, distribution, and pricing targeted to that single market segment. The primary advantage of this strategy is that it enables the organization to analyze the needs and wants of only one segment and then focus all its efforts on that segment. The primary disadvantage of concentration is that if demand in the segment declines, the organization's sales and financial position will also decline.

In the multi segment strategy, a company focuses its marketing efforts on two or more distinctmarket segments. The organization develops a distinct marketing mix for each segment. Thenthey develop marketing programs tailored to each of these segments. This strategy is advantageous because it may increase total sales with more marketing programs targeting more customers. The disadvantage is the higher costs, which stem from the need for multiple marketing programs that may include segment-specific product differentiation, promotions and communication, distribution/delivery channels, and pricing.

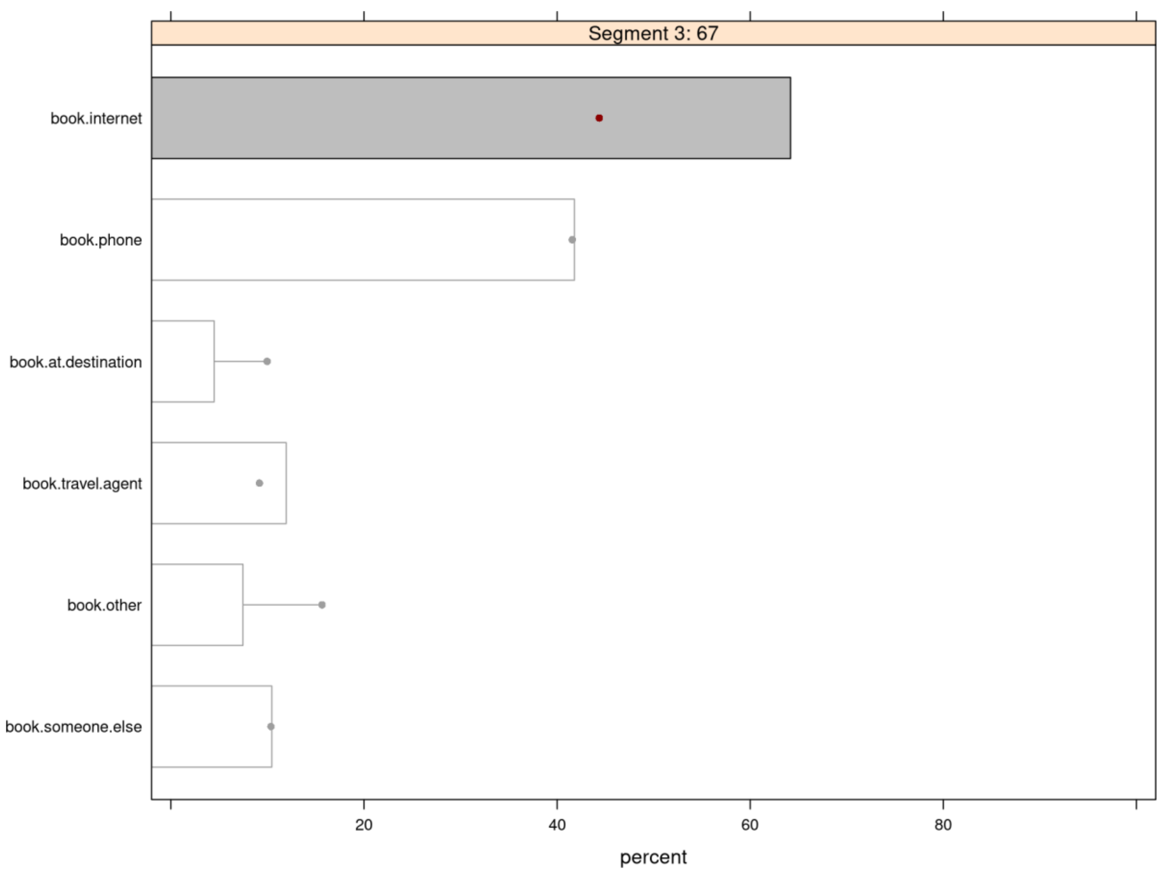
Step 9: Customizing the marketing mix

- **Product:** One of the key decisions an organization needs to make when developing the product dimension of the marketing mix, is to specify the product in view of customer needs. Often this does not imply designing an entirely new product, but rather modifying an existing one. Other marketing mix decisions that fall under the product dimension are naming the product, packaging it, offering or not offering warranties, and after sales support services.
- **Price:** Typical decisions an organization 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. Figure 1 shows the expenditures of segment 3 members on the right, and those of all other consumers on the left. Ideally, we would have information about actual expenditures across a wide range of expenditure categories, or information about price elasticity, or reliable information about the segment's willingness to pay for a range of products.



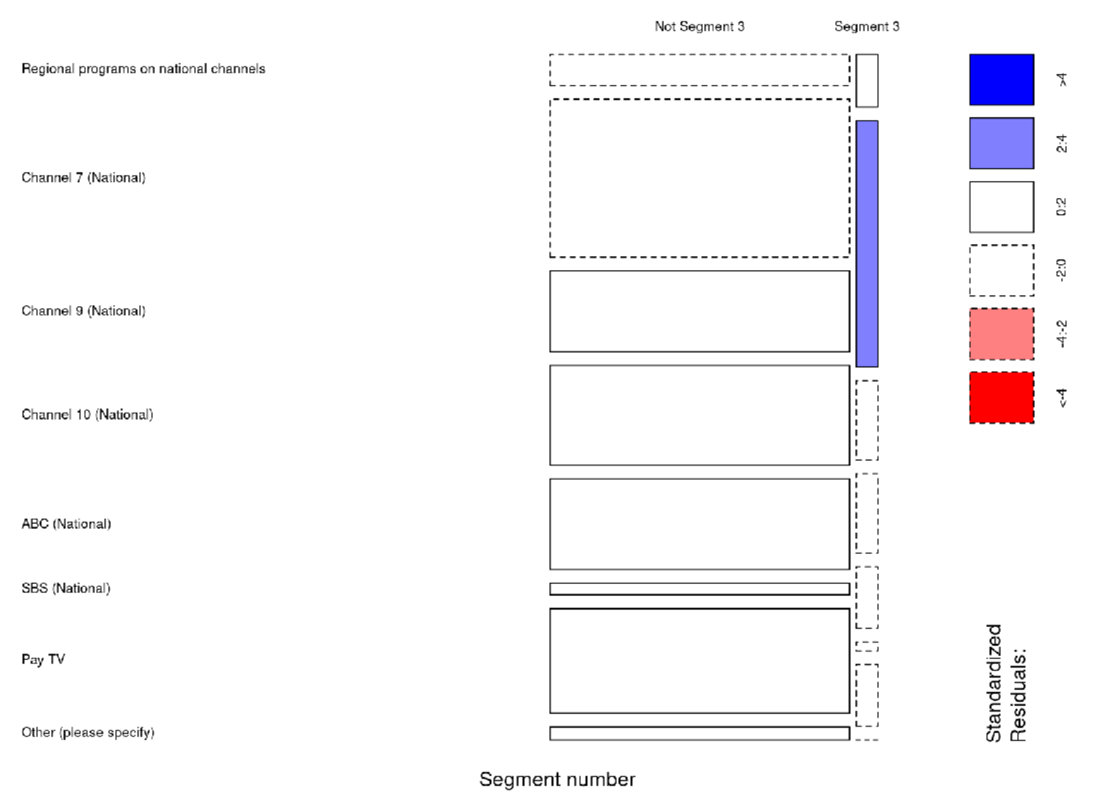
- **Place:** The key decision relating to the place dimension of the marketing mix is how to distribute the product to the customers. This includes answering questions such as: should the product be made available for purchase online or offline only or both; should the manufacturer sell directly to customers;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

  Returning to the example of members of segment 3 and the destination with a rich cultural heritage: the survey upon which the market segmentation analysis was based also asked survey respondents to indicate how they booked their accommodation during their last domestic holiday. Respondents could choose multiple options. This information is place valuable; knowing the booking preferences of members of segment 3 enables the destination to ensure that the museums, monuments & much, much more product is bookable through these very distribution channels.



- **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.

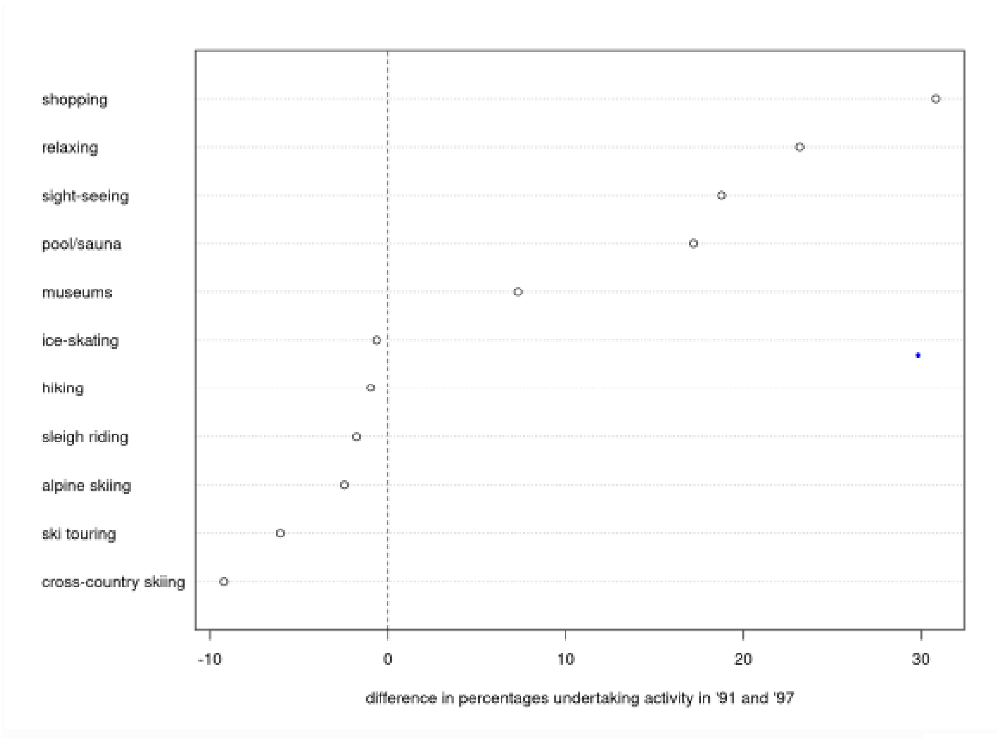
Looking at segment 3 again: we need to determine the best information sources for reaching members of segment 3 so we can inform them about the museums, monuments & much, much more product. We answer this question by comparing the information sources they used for the last domestic holiday, and by investigating their preferred TV stations.



Step 10: Evaluation and monitoring

Evaluation and monitoring are done by, determining which indicators will be used to capture market dynamics. The short term and long-term success indicators will be used to evaluate the market segmentation strategy**.**

(Fig.27) Example: The success of market segmentation depicted using Winter vacation activities dataset.



CASE STUDY – FAST FOOD DATSET

https://github.com/shanmugapriyadhanasekaran/bioinfo_practice/blob/main/mcdonalds-market-segmentation.ipynb

Thank You

PRIYA ROHIN SAGAR SAURABH