**Ten Steps of Market Segmentation Analysis**

**Step-1 summary points:**

**Implications of Committing to Market Segmentation:**

Before investing time and resources in a market segmentation analysis, it is important to understand the implications of pursuing a market segmentation strategy.

* Key implication is that the organisation needs to commit to the segmentation strategy on the long term.
* Segmenting a market is not free. There are costs of performing the research, fielding surveys, and focus groups, designing multiple packages, and designing multiple advertisements and communication messages.
* Required changes include the development of new products, the modification of existing products, changes in pricing and distribution channels used to sell the product, as well as all communications with the market.

**Implementation Barriers:**

* The first group of barriers relates to senior management.
* A second group of barriers relates to organisational culture.
* Another potential problem is lack of training.
* Another obstacle may be objective restrictions faced by the organisation, including lack of financial resources, or the inability to make the structural changes required.

Above all, a resolute sense of purpose and dedication is required, tempered by patience and a willingness to appreciate the inevitable problems which will be encountered in implementing the conclusions.

**Points to be remembered for successful implementation:**

* Ask if the organisation’s culture is market-oriented.
* Ask if the organisation is genuinely willing to change.
* Ask if the organisation takes a long-term perspective.
* Ask if the organisation is open to new ideas.
* Ask if communication across organisational units is good.
* Ask if the organisation is in the position to make significant (structural) changes.
* Ask if the organisation has sufficient financial resources to support a market segmentation strategy.
* Secure visible commitment to market segmentation from senior management.
* Secure active involvement of senior management in the market segmentation analysis.
* Secure required financial commitment from senior management.
* Ensure that the market segmentation concept is fully understood.
* Ensure that the implications of pursuing a market segmentation strategy are fully understood.
* Put together a team of 2-3 people (segmentation team) to conduct the market segmentation analysis.
* Ensure that a marketing expert is on the team.
* Ensure that a data expert is on the team.
* Ensure that a data analysis expert is on the team.
* Set up an advisory committee representing all affected organisational units.
* Ensure that the objectives of the market segmentation analysis are clear.
* Develop a structured process to follow during market segmentation analysis.
* Assign responsibilities to segmentation team members using the structured process.
* Ensure that there is enough time to conduct the market segmentation analysis without time pressure.

**Step-2 summary:**

In Step 2 the organisation must determine two sets of segment evaluation criteria.

1. **knock-out criteria.**

These criteria are the essential, non-negotiable features of segments that the organisation would consider targeting.

* The segment must be homogeneous.
* The segment must be distinct.
* The segment must be large enough
* The segment must be matching the strengths of the organisation
* Members of the segment must be identifiable
* The segment must be reachable

1. **Attractiveness criteria.**

These criteria are used to evaluate the relative attractiveness of the remaining market segments – those in compliance with the knock-out criteria.

**Step-3 summary:**

**Segmentation Variables:**

* Empirical data forms the basis of both commonsense and data-driven market segmentation.
* In commonsense segmentation, the segmentation variable is typically one single characteristic of the consumers in the sample.
* data-driven market segmentation is based not on one, but on multiple segmentation variables.

**Segmentation Criteria:** The most common segmentation criteria are geographic, socio demographic, psychographic and behavioural.

1. Geographic Segmentation:

* Typically – when geographic segmentation is used – the consumer’s location of residence serves as the only criterion to form market segments.
* 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 communication 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 necessarily mean that people share other characteristics relevant to marketers, such as benefits they seek when purchasing a product.

1. Socio-Demographic Segmentation:

* Typical socio-demographic segmentation criteria include age, gender, income and education.
* Socio-demographic segmentation criteria have the advantage that segment membership can easily be determined for every consumer.
* The disadvantage is it does not provide sufficient market insight for optimal segmentation decisions

1. Psychographic Segmentation:

* When people are grouped according to psychological criteria, such as their beliefs, interests, preferences, aspirations, or benefits sought when purchasing a product, the term psychographic segmentation is used.
* The psychographic approach has the advantage that it is generally more reflective of the underlying reasons for differences in consumer behaviour.
* The disadvantage of the psychographic approach is the increased complexity of determining segment memberships for consumers.

1. Behavioural Segmentation:

* A wide range of possible behaviours can be used for this purpose, including prior experience with the product, frequency of purchase, amount spent on purchasing the product on each occasion (or across multiple purchase occasions), and information search behaviour.
* The key advantage of behavioural approaches is that – if based on actual behaviour rather than stated behaviour or stated intended behaviour – the very behaviour of interest is used as the basis of segment extraction.
* The disadvantage is behavioural data is not always readily available, especially if the aim is to include in the segmentation analysis potential customers who have not previously purchased the product, rather than limiting oneself to the study of existing customers of the organisation.

**Data from Survey Studies:** A few key aspects that need to be considered when using survey data are discussed below.

1. Choice of Variables:

* Unnecessary variables must be avoided this makes questionnaires long and tedious for respondents, which, in turn, causes respondent fatigue which tends to provide responses of lower quality. It also increases the dimensionality of the segmentation problem.
* Noisy variables do not contribute any information necessary for the identification of the correct market segments. Instead, their presence makes it more difficult for the algorithm to extract the correct solution.
* Ask all necessary and unique questions, while resisting the temptation to include unnecessary or redundant questions.
* Redundant items are particularly problematic in the context of market segmentation analysis because they interfere substantially with most segment extraction algorithms’ ability to identify correct market segmentation solutions.

1. Response Options:

* Allow respondents to answer in only one of two ways, generate *binary or dichotomous* *data.*
* Allow respondents to select an answer from a range of unordered categories correspond to *nominal variables*.
* Allow respondents to indicate a number, such as age or nights stayed at a hotel, generate *metric data.*
* Respondents are asked to express – using five or seven response options – their agreement with a series of statements. This answer format generates *ordinal data*.

1. Response Styles:

*strongly agree, strongly disagree, neither agree nor disagree, agree with all statements*. These response styles affect segmentation results.

1. Sample Size:

Include a sufficient sample size given the number of segmentation variables (100 times the number of segmentation variables)

**Points to be remembered**

* contain all necessary items;
* contain no unnecessary items;
* contain no correlated items;
* contain high-quality responses;
* be binary or metric;
* be free of response styles;
* include responses from a suitable sample given the aim of the segmentation study; and
* include a sufficient sample size given the number of segmentation variables (100 times the number of segmentation variables)

**Data from Internal Sources:** Advantage of using internal data is that it is automatically generated and – if organisations are capable of storing data in a format that makes them easy to access – no extra effort is required to collect data.

Disadvantage of using internal data is that it may be systematically biased by over-representing existing customers.

**Data from Experimental Studies:** Experimental data can result from field or laboratory. It can also result from choice experiments or conjoint analyses. Conjoint studies and choice experiments result in information about the extent to which each attribute and attribute level affects choice. This information can also be used as a segmentation criterion.

**Step-4 summary:**

**Exploring Data**

Data exploration helps to (1) identify the measurement levels of the variables; (2) investigate the univariate distributions of each of the variables; and (3) assess dependency structures between variables.

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

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

**Descriptive Analysis:** Descriptive numeric and graphic representations provide insights into the data. we obtain a numeric summary of the data with command summary(). This command returns the range, the quartiles, and the mean for numeric variables. For categorical variables, the command returns frequency counts. The command also returns the number of missing values for each variable.

**Pre-Processing**

**Categorical Variables:**

* Two pre-processing procedures are often used for categorical variables. Merging levels of categorical variables before further analysis and converting categorical variables to numeric ones.
* Ordinal data can be converted to numeric data if it can be assumed that distances between adjacent scale points on the ordinal scale are approximately equal.
* Binary answer options are less prone to capturing response styles, and do not require data pre-processing. Pre-processing inevitably alters the data in some way.
* Binary variables can always be converted to numeric variables, and most statistical procedures work correctly after conversion if there are only two categories. Converting dichotomous ordinal or nominal variables to binary 0/1 variables is not a problem.

**Numeric Variables:**

* The range of values of a segmentation variable affects its relative influence in distance-based methods of segment extraction.
* To balance the influence of segmentation variables on segmentation results, variables can be standardised.
* Standardising variables means transforming them in a way that puts them on a common scale.
* Alternative standardisation methods may be required if the data contains observations located very far away from most of the data (outliers). In such situations, robust estimates for location and spread – such as the median and the inter quartile range – are preferable.

**Principal Components Analysis:**

* Principal components analysis (PCA) transforms a multivariate data set containing metric variables to a new data set with variables – referred to as principal components – which are uncorrelated and ordered by importance.
* Principal components analysis works off the covariance or correlation matrix of several numeric variables. If all variables are measured on the same scale, and have similar data ranges, it is not important which one to use. If the data ranges are different, the correlation matrix should be used (which is equivalent to standardising the data)
* In most cases, the transformation obtained from principal components analysis is used to project high-dimensional data into lower dimensions for plotting purposes.
* Sometimes principal components analysis is used for the purpose of reducing the number of segmentation variables before extracting market segments from consumer data.

**Step-5 summary:**

**Extracting Segments**

The most popular extraction methods used in market segmentation are the following.

1. **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).

**Distance Measures**

* 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(·, ·) 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 ⇔ x = y.

* In addition, most distance measures fulfil the so-called triangle inequality:

d(x, z) ≤ d(x, y) + d(y, z)

* The most common distance measures used in market segmentation analysis are*:*

***Euclidean distance***, ***Manhattan or absolute distance, Asymmetric binary distance.***

**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.
* For measuring the distance l(X, Y) between these two sets of observations.

***Single linkage:*** distance between the two closest observations of the two sets.

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

***Average linkage***: mean distance between observations of the two sets.

**Partitioning Methods**

* A partitioning clustering algorithm aiming to extract five market segments, in contrast, would only have to calculate between 5 and 5000 distances at each step of the iterative or stepwise process (the exact number depends on the algorithm used). In addition, if only a few segments are extracted, it is better to optimise specifically for that goal, rather than building the complete dendrogram and then heuristically cutting it into segments.
* ***k-Means and k-Centroid Clustering:***

The algorithm will always converge: the stepwise process used in a partitioning clustering algorithm will always lead to a solution. Reaching the solution may take longer for large data sets, and large numbers of market segments, however. The starting point of the process is random. Random initial segment representatives are chosen at the beginning of the process. Different random initial representatives (centroids) will inevitably lead to different market segmentation solutions.

In addition, the algorithm requires the specification of the number of segments. This sounds much easier than it is. The challenge of determining the optimal number of market segments is as old as the endeavour of grouping people into segments itself.

The key idea is to systematically repeat the extraction process for different numbers of clusters (or market segments), and then select the number of segments that leads to either the most stable overall segmentation solution, or to the most stable individual segment.

* ***“Improved” k-Means:***

The simplest improvement is to initialise k-means using “smart” starting values, rather than randomly drawing k consumers from the data set and using them as starting points. Using randomly drawn consumers is suboptimal because it may result in some of those randomly drawn consumers being located very close to one another, and thus not being representative of the data space. Using starting points that are not representative of the data space increases the likelihood of the k-means algorithm getting stuck in what is referred to as a local optimum. A local optimum is a good solution, but not the best possible solution. One way of avoiding the problem of the algorithm getting stuck in a local optimum is to initialise it using starting points evenly spread across the entire data space. Such starting points better represent the entire data set.

* ***Hard Competitive Learning:***

Hard competitive learning, also known as learning vector quantisation, differs from the standard k-means algorithm in how segments are extracted.

Although hard competitive learning also minimises the sum of distances from each consumer contained in the data set to their closest representative (centroid), the process by which this is achieved is slightly different. k-means uses all consumers in the data set at each iteration of the analysis to determine the new segment representatives (centroids). Hard competitive learning randomly picks one consumer and moves this consumer’s closest segment representative a small step into the direction of the randomly chosen consumer.

* ***Neural Gas and Topology Representing Networks:***

A variation of hard competitive learning is the neural gas algorithm proposed by Martinetz et al. (1993). Here, not only the segment representative (centroid) is moved towards the randomly selected consumer. Instead, also the location of the second closest segment representative (centroid) is adjusted towards the randomly selected consumer.

A further extension of neural gas clustering are topology representing networks.

* ***Self-Organising Maps:***

Another variation of hard competitive learning are self-organising maps, also referred to as self-organising feature maps or Kohonen maps.

Self-organising maps position segment representatives (centroids) on a regular grid, usually a rectangular or hexagonal grid.

The self-organising map algorithm is similar to hard competitive learning: a single random consumer is selected from the data set, and the closest representative for this random consumer moves a small step in their direction.

* ***Neural Networks:***

Auto-encoding neural networks for cluster analysis work mathematically differently than all cluster methods presented so far. The most popular method from this family of algorithms uses a so-called single hidden layer perceptron.

**Hybrid Approaches**

The basic idea behind hybrid segmentation approaches is to first run a partitioning algorithm because it can handle data sets of any size. But the partitioning algorithm used initially does not generate the number of segments sought. Rather, a much larger number of segments is extracted. Then, the original data is discarded and only the centres of the resulting segments (centroids, representatives of each market segment) and segment sizes are retained, and used as input for the hierarchical cluster analysis. At this point, the data set is small enough for hierarchical algorithms, and the dendrogram can inform the decision how many segments to extract.

* ***Two-Step Clustering:***

The two steps consist of run a partitioning procedure followed by a hierarchical procedure. The procedure has been used in a wide variety of application areas, including internet access types of mobile phone users, segmenting potential nature-based tourists based on temporal factors, identifying and characterising potential electric vehicle adopters, and segmenting travel related risks.

* ***Bagged Clustering:***

In bagged clustering, we first cluster the bootstrapped data sets using a partitioning algorithm. The advantage of starting with a partitioning algorithm is that there are no restrictions on the sample size of the data. Next, we discard the original data set and all bootstrapped data sets. We only save the cluster centroids (segment respresentatives) resulting from the repeated partitioning cluster analyses. These cluster centroids serve as our data set for the second step: hierarchical clustering. The advantage of using hierarchical clustering in the second step is that the resulting dendrogram may provide clues about the best number of market segments to extract.

Bagged clustering consists of five steps starting with a data set X of size n:

1. Create b bootstrap samples of size n by drawing with replacement consumers from the data set (using b = 50 or 100 bootstrap samples works well).

2. Repeat the preferred partitioning method for each bootstrap sample, generating b × k cluster centres (centroids, representatives of market segments) with k representing the number of clusters (segments). Leisch (1999) shows that the exact number of clusters k selected is not important, as long as the number selected is higher than the number of segments expected to exist in the data. If k is larger than necessary, segments artificially split up in this step are merged during hierarchical clustering.

3. Use all cluster centres resulting from the repeated partitioning analyses to create a new, derived data set. Discard the original data. In the subsequent steps, replace the original data with the derived data set containing the cluster centres (centroids, representatives of market segments). It is for this reason that bagged clustering can deal with large data sets; it effectively discards the large data set once it has successfully extracted a number of cluster centres.

4. Calculate hierarchical clustering using the derived data set.

5. Determine the final segmentation solution by selecting a cut point for the dendrogram. Then, assign each original observation (consumer in the data set) to the market segment the representative of which is closest to that particular consumer

1. **Model-Based Methods**

These methods formulate a concise stochastic model for the market segments.

Model-based methods can be seen as selecting a general structure, and then finetuning 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 can be written down in a more formal way.

**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:

**z ∼ Multinomial(π ).**

**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:

**f (y|x,θz).**

**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.

* ***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 elements of y, the segmentation variables, could be vacation activities where a value of 1 indicates that a tourist undertakes this activity, and a value of 0 indicates that they do not.

**Finite Mixtures of Regressions:**

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.

**Extensions and Variations:**

* 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. As a consequence, finite mixture models can accommodate a wide range of different data characteristics: for metric data we can use mixtures of normal distributions, for binary data we can use mixtures of binary distributions.
* For nominal variables, we can use mixtures of multinomial distributions or multinomial logit models.
* For ordinal variables, several models can be used as the basis of mixtures. Ordinal variables are tricky because they are susceptible to containing response styles.
* Mixture models also allow to simultaneously include segmentation and descriptor variables. Segmentation variables are used for grouping, and are included in the segment-specific model as usual. Descriptor variables are used to model differences in segment sizes, assuming that segments differ in their composition with respect to the descriptor variables.

**Algorithms with Integrated Variable Selection**

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.

* ***Biclustering Algorithms:***

The biclustering algorithm which extracts these biclusters follows a sequence of steps. The starting point is a data matrix where each row represents one consumer and each column represents a binary segmentation variable:

**Step 1** First, rearrange rows (consumers) and columns (segmentation variables) of the data matrix in a way to create a rectangle with identical entries of 1s at the top left of the data matrix. The aim is for this rectangle to be as large as possible.

**Step 2** Second, assign the observations (consumers) falling into this rectangle to one bicluster, as illustrated by the grey shading. The segmentation variables defining the rectangle are active variables (A) for this bicluster.

**Step 3** Remove from the data matrix the rows containing the consumers who have been assigned to the first bicluster. Once removed, repeat the procedure from step 1 until no more biclusters of sufficient size can be located.

* ***Variable Selection Procedure for Clustering Binary Data (VSBD):***

The algorithm works as follows:

**Step 1** Select only a subset of observations with size φ ∈ (0, 1] times the size of the original data set. Brusco suggests to use φ = 1 if the original data set contains less than 500 observations, 0.2 ≤ φ ≤ 0.3 if the number of observations is between 500 and 2000 and φ = 0.1 if the number of observations is at least 2000.

**Step 2** For a given number of variables V, perform an exhaustive search for the set of V variables that leads to the smallest within-cluster sum-of-squares criterion. The value for V needs to be selected small for the exhaustive search to be computationally feasible. Brusco suggests using V = 4, but smaller or larger values may be required depending on the number of clusters k, and the number of variables p. The higher the number of clusters, the larger V should be to capture the more complex clustering structure. The higher p, the smaller V needs to be to make the exhaustive search computationally feasible.

**Step 3** Among the remaining variables, determine the variable leading to the smallest increase in the within-cluster sum-of-squares value if added to the set of segmentation variables.

**Step 4** Add this variable if the increase in within-cluster sum-of-squares is smaller than the threshold. The threshold is δ times the number of observations in the subset divided by 4. δ needs to be in [0, 1]. Brusco suggests a default δ value of 0.5.

* ***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.

**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.

* ***Cluster Indices:***

Because market segmentation analysis is exploratory, data analysts need guidance to make some of the most critical decisions, such as selecting the number of market segments to extract. So-called cluster indices represent the most common approach to obtaining such guidance. Cluster indices provide insight into particular aspects of the market segmentation solution. Which kind of insight, depends on the nature of the cluster index used.

**Internal cluster indices** are calculated on the basis of one single market segmentation solution, and use information contained in this segmentation solution to offer guidance. An example for an internal cluster index is the sum of all distances between pairs of segment members. The lower this number, the more similar members of the same segment are. Segments containing similar members are attractive to users.

**External cluster indices** cannot be computed on the basis of one single market segmentation solution only. Rather, they require another segmentation as additional input. The external cluster index measures the similarity between two segmentation solutions. If the correct market segmentation is known, the correct assignment of members to segments serves as the additional input. The correct segment memberships, however, are only known when artificially generated data is being segmented.

* ***Gorge Plots:***

A simple method to assess how well segments are separated, is to look at the distances of each consumer to all segment respresentatives.

If natural, well-separated market segments are present in the data, we expect the gorge plot to contain many very low and many very high values. This is why this plot is referred to as gorge plot. Optimally, it takes the shape of a gorge with a peak to the left and a peak to the right.

* ***Global Stability Analysis:***

An alternative approach to data structure analysis that can be used for both distance and model-based segment extraction techniques is based on resampling methods. Resampling methods offer insight into the stability of a market segmentation solution across repeated calculations. To assess the global stability of any given segmentation solution, several new data sets are generated using resampling methods, and a number of segmentation solutions are extracted.

The following guidelines for assessing global stability boxplots based on the inspection of a wide range of empirical data sets:

• Indicative of natural segments are global stability boxplots with high stability and low variance of the overall market segmentation solution for at least a limited range of numbers of segments, and a distinct drop in global stability for all other numbers of segments.

• Indicative of reproducible segmentation are global stability boxplots – which starting from a reasonable high stability – show a gradual decline in the global stability of the market segmentation solution with increasing numbers of segments.

• Indicative of constructive segmentation are stability boxplots which display near constant low stability across the overall market segmentation solutions for all numbers of segments.

* ***Segment Level Stability Analysis:***

Choosing the globally best segmentation solution does not necessarily mean that this particular segmentation solution contains the single best market segment. Relying on global stability analysis could lead to selecting a segmentation solution with suitable global stability, but without a single highly stable segment. It is recommendable, therefore, to assess not only global stability of alternative mar- 7.5 Data Structure Analysis 167 ket segmentation solutions, but also segment level stability of market segments contained in those solutions to protect against discarding solutions containing interesting individual segments from being prematurely discarded. After all, most organisations only need one single target segment.

1. Segment Level Stability Within Solutions (SLSW )
2. Segment Level Stability Across Solutions (SLSA)

**Step-6 summary:**

**Profiling Segments**

The aim of the profiling step is to get to know the market segments resulting from the extraction step. Profiling is only required when data-driven market segmentation is used. For commonsense segmentation, the profiles of the segments are predefined.

**Identifying Key Characteristics of Market Segments:** At the profiling stage, we inspect a number of alternative market segmentation solutions. This is particularly important if no natural segments exist in the data, and either a reproducible or a constructive market segmentation approach has to be taken. Good profiling is the basis for correct interpretation of the resulting segments. Correct interpretation, in turn, is critical to making good strategic marketing decisions.

**Traditional Approaches to Profiling Market Segments:** Data-driven segmentation solutions are usually presented to users (clients, managers) in one of two ways:

1. as high level summaries simplifying segment characteristics to a point where they are misleadingly trivial, or
2. as large tables that provide, for each segment, exact percentages for each segmentation variable.

**Segment Profiling with Visualisations:** Visualisations 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. Visualisations of solutions assist the data analyst and user with this task.

* Identifying Defining Characteristics of Market Segments:
* A good way to understand the defining characteristics of each segment is to produce a *segment profile plot*.
* The segment profile plot is a so-called *panel plot.*
* Good visualisations facilitate interpretation by managers who make long-term strategic decisions based on segmentation results. Such long-term strategic decisions imply substantial financial commitments to the implementation of a segmentation strategy. Good visualisations, therefore, offer an excellent return on investment
* Assessing Segment Separation:
* Segment separation can be visualised in a *segment separation plot*. The segment separation plot depicts – for all relevant dimensions of the data space – the overlap of segments.
* 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 quick overview of the data situation, and the segmentation solution.