Task-1 (a) : Market Segmentation Summary

Team 1

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Step 1: Deciding (not) to Segment

Before embarking on a market segmentation strategy, it is crucial to understand its long-term implications and potential barriers to successful implementation.

Implications of Committing to Market Segmentation:

- Long-term commitment: Market segmentation is a sustained endeavor, not a short-term project. Organizations must be prepared to make substantial changes in products, pricing, distribution, and communication strategies to cater to different segments.
- Organizational restructuring: Targeting multiple segments may necessitate internal restructuring, such as forming strategic business units aligned with market segments.
- Resource allocation: Market segmentation requires investments in research, surveys, focus groups, product development, and marketing campaigns tailored to each segment.

Implementation Barriers:

- Senior management involvement: Lack of leadership, commitment, and involvement from senior management can hinder the successful implementation of market segmentation.
- Organizational culture: Factors like lack of market orientation, resistance to change, poor communication, and short-term thinking can impede segmentation efforts.
- Lack of training: Insufficient understanding of market segmentation concepts and implications among senior management and the segmentation team can lead to failed attempts.
- Resource constraints: Limited financial resources, lack of qualified personnel, or inability to make necessary structural changes can pose significant obstacles.
- Process-related barriers: Absence of clear objectives, poor planning, inadequate processes, lack of responsibility allocation, and time pressure can hinder the effectiveness of market segmentation analysis.
- Lack of understanding: Failure to comprehend the market segmentation concept and its implications can lead to misinterpretations and poor decision-making.

Implications:

- Organizations should carefully assess their readiness for market segmentation, considering their commitment, resources, and organizational culture.

- Barriers to successful implementation should be identified and addressed proactively.
- Training and education programs may be necessary to ensure a shared understanding of market segmentation concepts and implications across the organization.
- A structured and well-defined process should be established to guide the market segmentation analysis and implementation.

Step 2: Specifying the Ideal Target Segment

Segment evaluation is the process of assessing the attractiveness and feasibility of different market segments based on predefined criteria. It helps organizations identify the segments that are most aligned with their goals and objectives, and that offer the greatest potential for success. There are two types of segment evaluation criteria:

1. **Knock-Out Criteria:** Knock-out criteria are essential, non-negotiable features that segments must possess in order to be considered for targeting. These criteria are typically related to basic characteristics of the segment, such as size, homogeneity, and accessibility. If a segment does not meet the knock-out criteria, it is automatically eliminated from further consideration.Common knock-out criteria include:
    - Size: The segment should be large enough to be worth targeting.
    - Homogeneity:Members of the segment should be similar to one another in terms of relevant characteristics.
    - Distinctness:Members of the segment should be distinctly different from members of other segments.
    - Identifiability:It should be possible to identify and reach members of the segment.
    - Reachability:There should be a way to communicate with and deliver products or services to segment members.
    - Matching the strengths of the organization:The organization should have the capability to satisfy segment members' needs.

2. **Attractiveness Criteria:**
    Attractiveness criteria are used to evaluate the relative attractiveness of segments that comply with the knock-out criteria. These criteria are more subjective and can vary depending on the organization's specific goals and objectives. Common attractiveness criteria include:
    - Growth potential:The segment should have the potential for growth in terms of size, purchasing power, or other relevant metrics.
    - Profitability:The segment should be profitable to serve.
    - Competitive intensity:The level of competition within the segment should be manageable.
    - Brand fit:The segment should align well with the organization's brand image and values.

- Customer loyalty:The segment should have a high level of customer loyalty or the potential for developing it.

Implementing a Structured Process:
To ensure objectivity and consistency in evaluating market segments, it is recommended to follow a structured process. This typically involves:

- Identifying a set of relevant segment attractiveness criteria.
- Assigning weights to each criterion to reflect its relative importance.
- Collecting data on each segment's performance against the selected criteria.
- Evaluating segments based on their attractiveness scores and selecting the most attractive ones as target segments.

Implications:
To conduct segment evaluation effectively, organizations should:

- Convene a segmentation team meeting to discuss and agree on both knock-out criteria and attractiveness criteria.
- Present the criteria to the advisory committee for discussion and adjustment, if necessary.
- Individually study available criteria for segment attractiveness assessment and agree on a subset of no more than six criteria.
- Distribute points across the segment attractiveness criteria to reflect their relative importance.
- Discuss weightings with other segmentation team members and agree on a weighting.
- Present the selected segment attractiveness criteria and the proposed weights to the advisory committee for discussion and adjustment, if required.

Step 3: Collecting Data

Segmentation Variables:

- Market segmentation is based on empirical data. Segmentation variables are the variables used to split the sample into market segments.Commonly, segmentation studies rely on self-reported data.
- Commonsense segmentation variables represent variations between consumers in terms of a single characteristic or a set of characteristics.
- Data-driven market segmentation is based on multiple segmentation variables, which are then used to identify naturally existing or artificially created segments that have utility for the organization.
- 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 naturally existing, or artificially creating market segments useful to the organisation.

Segmentation Criteria:
Before extracting segments, the organization needs to choose a segmentation criterion: geographic, sociodemographic, psychographic, or behavioral.

1. **Geographic Segmentation:** It is basically dividing the market based on geographic boundaries, such as countries, regions, states, or cities.
   Geographic segmentation is the simplest and most straightforward form of market segmentation. It is often used as a starting point for further segmentation. Geographic segmentation can be useful for targeting marketing messages and distribution channels to specific regions. It is easy to implement, but does not consider that consumers may share characteristics that are more relevant to the marketing strategy.
   E.g. A travel agency might segment its market by country or region to target different travel destinations and interests.

2. **Sociodemographic Segmentation:** It is segmenting the market based on demographic characteristics such as age, gender, income, education, and family size.
   Sociodemographic segmentation is a widely used form of market segmentation. It is based on the assumption that consumers with similar demographic characteristics have similar needs and wants. Sociodemographic segmentation can be useful for targeting marketing messages, products, and services to specific demographic groups. It is useful in some industries, though may not provide sufficient insight into product preferences.
   E.g. (a) A cosmetics company might segment its market by age group to target different skincare and makeup needs, (b) A car manufacturer might segment its market by income level to target different vehicle types and price ranges.

3. **Psychographic Segmentation:** It is dividing the market based on psychological characteristics such as values, attitudes, beliefs, interests, and personality traits.
   Psychographic segmentation is a more sophisticated form of market segmentation. It is based on the assumption that consumers with similar psychological characteristics have similar needs and wants. Psychographic segmentation can be useful for targeting marketing messages, products, and services to specific psychographic groups. It is more complex than geographic or sociodemographic methods, but can provide more relevant insights.
   E.g. (a) A political party might segment its market by values to target different policy positions and candidates, (b) A clothing retailer might segment its market by lifestyle to target different fashion trends and preferences.

4. **Behavioral Segmentation:** It is basically segmenting the market based on consumer behavior, including purchase patterns, usage patterns, and brand loyalty.
   Behavioral segmentation is a powerful form of market segmentation. It is based on the assumption that consumers with similar behavior have similar needs and wants.

Behavioral segmentation can be used to target marketing messages, products, and services to specific behavioral groups. It is advantageous because it focuses on actual behavior relevant to the product or service.
E.g. (a) A telecommunications company might segment its market by usage patterns to target different calling plans and data plans, (b) A credit card company might segment its market by brand loyalty to target different rewards programs and benefits.

Data from Survey Studies:

- Surveys are the most common source of data for market segmentation studies. However, survey data is more susceptible to biases, even when following psychometric principles.
- We should carefully select segmentation variables to avoid noisy or irrelevant variables that can hinder the segmentation process and the identification of correct segments.
- We should pay attention to the choice of response options, ensuring that they are appropriate for the subsequent segmentation analysis.
- We should minimize the risk of capturing response styles that can provide misleading results.
- We should ensure a sufficient sample size to enable the algorithm to extract meaningful segments. An insufficient sample size can hinder the identification of the correct number and characteristics of segments.

Data from Internal Sources:

- Internal data, such as scanner data or online purchase data, can provide valuable information for market segmentation.
- The advantage of internal data is that it represents actual consumer behavior. The disadvantage is that it may be systematically biased towards existing customers.

Data from Experimental Studies:

- Experimental data, derived from field or laboratory experiments, can also serve as a basis for market segmentation analysis.
- Choice experiments or conjoint analyses present consumers with specific product stimuli to reveal attribute preferences.
- The data collected from these experiments can be used as segmentation variables or to understand the importance of different attributes in segment preferences.

Implications:

The organization should:

- Choose the right segmentation criterion: Consider: the nature of the product or service, the target audience, the available data and the desired level of granularity in segmentation.

- Use a variety of segmentation variables: Consider: combining multiple variables to create more targeted segments, and avoiding an overreliance on a single variable
- Ensure that the segmentation variables are relevant and meaningful: Consider: whether the variables are related to the product or service, and whether the variables are actionable (i.e., can be used to develop marketing strategies)
- Use a sample size that is large enough to ensure statistical significance: Consider: the desired level of confidence, the variability of the data, and the complexity of the segmentation model
- Use a data collection method that is appropriate for the segmentation variables: Consider: the type of data to be collected, the target audience, and the available resources
- Clean and prepare the data before conducting the segmentation analysis: Consider: removing duplicate or incomplete data, dealing with missing values, and transforming the data into a usable format
- Use a segmentation algorithm that is appropriate for the data and the desired segmentation goals: Consider: the number of segments to extract, the desired level of homogeneity within segments, and the desired level of heterogeneity between segments

Step 5: Extracting Segments

Grouping Consumers:

- Market segmentation analysis is exploratory, and consumer data sets are typically unstructured. Therefore, results from any extraction method depend heavily on the assumptions made about the structure of the segments.
- Many segmentation methods used to extract market segments come from cluster analysis, and it is important to match the data analytic features of the resulting clustering with the desired requirements.
- Different algorithms impose different structures on the extracted segments, and it is important to understand how these structures will impact the segmentation solution.
- Data and Segment Characteristics Informing Extraction Algorithm Selection: Data set characteristics such as size, scale level of segmentation variables, and special structure can inform the selection of an extraction algorithm. Segment characteristics such as similarities within segments, differences between segments, and number and size of segments should also be considered.

This step involves identifying groups of consumers with similar needs or behavior, which are referred to as market segments. Two main approaches are used to extract market segments:
1. Distance-Based Methods: Distance-based methods for market segmentation are a group of techniques that use measures of similarity or dissimilarity between observations to group them into segments, or clusters. These methods are often used when the data is high-dimensional and it is difficult to visually separate the observations into distinct groups.

1.1 Distance Measures: Distance measures are used to quantify the similarity or dissimilarity between two observations. There are a wide variety of distance measures available, each with its own advantages and disadvantages. The most commonly used distance measures in market segmentation are:

1. Euclidean distance: Euclidean distance between two observations is the square root of the sum of the squared differences between their values on each variable. This is the most common distance measure, and it is often used when the variables are continuous and normally distributed.

2. Manhattan distance: Manhattan distance between two observations is the sum of the absolute differences between their values on each variable. This distance measure is often used when the variables are discrete or when the data is sparse.

3. Asymmetric binary distance: Asymmetric binary distance is a measure of dissimilarity between two binary vectors, that is, vectors that contain only 0s and 1s. It takes into account the fact that a 1 in one vector and a 0 in the other vector is more dissimilar than a 0 in both vectors or a 1 in both vectors. The asymmetric binary distance is 0 if both vectors are 0, and it is equal to the number of 1s that the two vectors have in common divided by the total number of 1s in either vector otherwise.

1.2 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). The hierarchy of clusters can be represented as a dendrogram, which visually displays the relationships between the clusters.
- Divisive hierarchical clustering methods start with the complete data set X and splits it into two market segments in a first step. Then, each of the segments is again split into two segments. This process continues until each consumer has their own market segment.
- Agglomerative hierarchical clustering approaches the task from the other end. The starting point is each consumer representing their own market segment (n singleton clusters). Step-by-step, the two market segments closest to one another are merged until the complete data set forms one large market segment.
- Numerous algorithms have been proposed for both strategies. The unifying framework for agglomerative clustering – which was developed in the seminal paper by Lance and Williams (1967) – contains most methods still in use today.
- In each step, standard implementations of hierarchical clustering perform the optimal step. This leads to a deterministic algorithm. This means that every time the hierarchical clustering algorithm is applied to the same data set, the exactly same sequence of nested partitions is obtained.

- There is no correct combination of distance and linkage method. Clustering in general, and hierarchical clustering in specific, are exploratory techniques. Different combinations can reveal different features of the data.
- A very popular alternative hierarchical clustering method is named after Ward (1963), and based on squared Euclidean distances. Ward clustering joins the two sets of observations (consumers) with the minimal weighted squared Euclidean distance between cluster centers.

1.3 Partitioning Methods:
Partitioning clustering methods divide the set of observations into subsets such that consumers assigned to the same market segment are as similar to one another as possible, while consumers belonging to different market segments are as dissimilar as possible.

1.3.1 k-Means and k-Centroid Clustering: The most popular partitioning method is k-means clustering. The representative of a market segment is referred to in many partitioning clustering algorithms as the centroid. For the k-means algorithm based on the squared Euclidean distance, the centroid consists of the column-wise mean values across all members of the market segment. The data set contains observations (consumers) in rows, and variables (behavioural information or answers to survey questions) in columns. The column-wise mean, therefore, is the average response pattern across all segmentation variables for all members of the segment.
The following generic algorithm represents a heuristic for solving the optimisation problem of dividing consumers into a given number of segments such that consumers are similar to their fellow segment members, but dissimilar to members of other segments. This algorithm is iterative; it improves the partition in each step, and is bound to converge, but not necessarily to the global optimum. It involves five steps:

1. Specify the desired number of segments k.
2. Randomly select k observations (consumers) from data set X and use them as initial set of cluster centroids $C = \{c_1,...,c_k\}$. If five market segments are being extracted, then five consumers are randomly drawn from the data set, and declared the representatives of the five market segments.
3. Assign each observation xi to the closest cluster centroid to form a partition of the data, that is, k market segments $S_1,\ldots,S_k$ where $S_j = \{x \in X \mid d(x,c_j) \leq d(x,c_h), 1 \leq h \leq k\}$. This means that each consumer in the data set is assigned to one of the initial segment representatives.
4. Recompute the cluster centroids by holding cluster membership fixed, and minimising the distance from each consumer to the corresponding cluster centroid. For squared Euclidean distance, the optimal centroids are the cluster-wise means, for Manhattan distance cluster-wise medians, resulting in the so-called k-means and k-medians procedures, respectively.

5. Repeat from step 3 until convergence or a pre-specified maximum number of iterations is reached.

1.3.2 Improved k-Means: Many attempts have been made to refine and improve the k-means clustering algorithm. 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.

Steinley and Brusco (2007) compare 12 different strategies proposed to initialise the k-means algorithm. Based on an extensive simulation study using artificial data sets of known structure, Steinley and Brusco conclude that the best approach is to randomly draw many starting points, and select the best set. The best starting points are those that best represent the data. Good representatives are close to their segment members; the total distance of all segment members to their representatives is small. Bad representatives are far away from their segment members; the total distance of all segment members to their representatives is high.

1.3.3 Hard Competitive Learning: Hard competitive learning, also known as learning vector quantisation (e.g. Ripley 1996), 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.

As a consequence of this procedural difference, different segmentation solutions can emerge, even if the same starting points are used to initialise the algorithm.

It is also possible that hard competitive learning finds the globally optimal market segmentation solution, while k-means gets stuck in a local optimum (or the other way around). Neither of the two methods is superior to the other; they are just different.

1.3.4 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. However, the location of the second closest representative is adjusted to a smaller degree than that of the primary representative.

1.3.5 Self-Organising Maps: Another variation of hard competitive learning are self-organising maps (Kohonen 1982, 2001), 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.

In addition, representatives which are direct grid neighbours of the closest representative move in the direction of the selected random consumer. The process is repeated many times; each consumer in the data set is randomly chosen multiple times, and used to adjust the location of the centroids in the Kohonen map.

What changes over the many repetitions, however, is the extent to which the representatives are allowed to change. The adjustments get smaller and smaller until a final solution is reached.

The advantage of self-organising maps over other clustering algorithms is that the numbering of market segments is not random. Rather, the numbering aligns with the grid along which all segment representatives (centroids) are positioned.

The price paid for this advantage is that the sum of distances between segment members and segment representatives can be larger than for other clustering algorithms. The reason is that the location of representatives cannot be chosen freely. Rather, the grid imposes restrictions on permissible locations.

1.3.6 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. The network has three layers. The input layer takes the data as input. The output layer gives the response of the network. In the case of clustering this is the same as the input. In-between the input and output layer is the so-called hidden layer. It is named hidden because it has no connections to the outside of the network.

k-means clustering and hard competitive learning produce crisp segmentations, where each consumer belongs to exactly one segment. Neural network clustering is an example of a so-called fuzzy segmentation with membership values between 0 (not a member of this segment) and 1 (member of only this segment). Membership values between 0 and 1 indicate membership in multiple segments.

1.4 Hybrid Approaches:

- Several approaches combine hierarchical and partitioning algorithms in an attempt to compensate the weaknesses of one method with the strengths of the other. The strengths of hierarchical cluster algorithms are that the number of market segments to be extracted does not have to be specified in advance, and that similarities of market segments can be visualised using a dendrogram. The biggest disadvantage of hierarchical clustering algorithms is that standard implementations require substantial memory capacity, thus restricting the possible sample size of the data for applying these methods.
- The strength of partitioning clustering algorithms is that they have minimal memory requirements during calculation, and are therefore suitable for segmenting large data sets. The disadvantage of partitioning clustering algorithms is that the number of market segments to be extracted needs to be specified in advance. Partitioning algorithms also do not enable the data analyst to track changes in segment membership across segmentation solutions with different number of segments because these segmentation solutions are not necessarily nested.

1.4.1 Two-Step Clustering: IBM SPSS (IBM Corporation 2016) implemented a procedure referred to as two step clustering (SPSS 2001). The two steps consist of run a partitioning procedure followed by a hierarchical procedure.

1.4.2 Bagged Clustering: Bagged clustering (Leisch 1998, 1999) also combines hierarchical clustering algo rithms and partitioning clustering algorithms, but adds bootstrapping (Efron and Tibshirani 1993). Bootstrapping can be implemented by random drawing from the data set with replacement. That means that the process of extracting segments is repeated many times with randomly drawn (bootstrapped) samples of the data. Bootstrapping has the advantage of making the final segmentation solution less dependent on the exact people contained in consumer data. 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 is suitable in the following circumstances (Dolnicar and Leisch 2004;Leisch1998):

- If we suspect the existence of niche markets.
- If we fear that standard algorithms might get stuck in bad local solutions.
- If we prefer hierarchical clustering, but the data set is too large.

Bagged clustering can identify niche segments because hierarchical clustering captures market niches as small distinct branches in the dendrogram. The increased chance of arriving at a good segmentation solution results from:

- Drawing many bootstrap samples from the original data set,
- Repeating the k-means analysis– or any other partitioning algorithm– many times to avoid a suboptimal initialisation (the random choice of initial segment representatives),
- Using only the centroids resulting from the k-means studies in the second (hierarchical) step of the analysis, and
- Using the deterministic hierarchical analysis in the final step.

2. Model-Based Methods: Model-based methods are a class of market segmentation techniques that use statistical models to identify and extract market segments.
Unlike distance-based methods, which rely on similarities or distances between data points, model-based methods assume that the true market segmentation solution has two general properties:

1. Each market segment has a certain size.
2. Members of each market segment have segment-specific characteristics.

2.1 Finite Mixtures of Distributions: Finite mixtures of distributions is a model-based segmentation method that assumes that the data can be represented by a mixture of probability distributions, where each distribution corresponds to a different market segment. The parameters of the mixture model are estimated using maximum likelihood or Bayesian methods.

2.1.1 Normal Distributions: A mixture of normal distributions is a special case of finite mixtures of distributions where the underlying distributions are normal distributions. This method is commonly used when the segmentation variables are continuous, such as age, income, or spending habits.
E.g. A mixture of normal distributions can be used for market segmentation when the segmentation variables are metric, such as money spent on different consumption categories, time spent engaging in different vacation activities, or body measurements for the segments of different clothes sizes, etc.

2.1.2 Binary Distributions: A mixture of binary distributions is another special case of finite mixtures of distributions where the underlying distributions are binary distributions. This method is commonly used when the segmentation variables are binary, such as gender or product ownership. For binary data,finite mixtures of binary distributions,sometimes also referred to as Latent class models or latent class analysis (BhatnagarandGhose2004;Kemperman andTimmermanns2006;Campbell et al. 2014) are popular.
The mixture model assumes that respondents in different segments have different probabilities of undertaking certain activities.

2.2 Finite Mixtures of Regressions: Finite mixtures of regressions is a model-based segmentation method that assumes that the relationship between the dependent variable and the independent variables is different for different market segments. This method is commonly used when the goal is to identify segments with different preferences, attitudes, or behaviors.
Finite mixtures 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 being different for different market segments.

2.3 Extensions and Variations:
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

There are several extensions and variations of finite mixture models that can be used for market segmentation. These include:

- Mixtures of mixed-effects models: This method allows for heterogeneity within segments by assuming that the parameters of the mixture model can vary across individuals.
- Dynamic latent change models: This method is used to track changes in market segments over time.
- Mixture models for simultaneous segmentation and descriptor variables: This method allows for the inclusion of descriptor variables that are used to model the sizes and compositions of the market segments.

Algorithms with Integrated Variable Selection:
This section focuses on algorithms designed for market segmentation analysis that incorporate a variable selection mechanism during segment extraction. The aim is to obtain a good clustering solution while simultaneously identifying a subset of relevant variables.

- Biclustering Algorithms: Biclustering algorithms aim to identify subsets of consumers and variables (biclusters) that have a specific pattern, such as consumers who all share a common set of values for a subset of variables. This approach can be useful for discovering hidden patterns in high-dimensional data sets. Several biclustering algorithms exist, each with its own strengths and limitations. One popular algorithm is the repeated Bimax algorithm, which searches for biclusters with a checkerboard pattern, where there is a clear distinction between the values of consumers and variables within the bicluster and outside of it.

- Variable Selection Procedure for Clustering Binary Data (VSBD): The VSBD algorithm is designed specifically for clustering binary data sets. It uses a two-step procedure that first identifies a small subset of variables that are most informative for distinguishing between segments and then iteratively adds additional variables until a stopping criterion is met. The algorithm can help identify a parsimonious set of variables that can be used for effective segmentation.
- Variable Reduction: Factor-Cluster Analysis: Factor-cluster analysis is a two-step procedure that involves factor analyzing the segmentation variables to reduce their dimensionality and then using the resulting factor scores for clustering. This approach can be useful when there are a large number of segmentation variables, but it can also lead to a loss of information. Therefore, it is important to carefully consider whether factor-cluster analysis is appropriate for a particular data set.

Data Structure Analysis:

Data structure analysis aims to assess the suitability of a data set for market segmentation and to guide the selection of the number of segments to extract.

- Cluster Indices: Cluster indices are a common approach to data structure analysis. They provide numerical measures that evaluate the quality of a clustering solution, such as the compactness of segments and the separation between segments. Internal cluster indices assess the quality of a clustering solution based on the data within the segments, while external cluster indices compare the results of different clustering solutions. Common internal cluster indices include the sum of within-cluster distances, the Ball-Hall index, the Calinski-Harabasz index, and the Silhouette coefficient. Common external cluster indices include the Jaccard index, the Rand index, and the adjusted Rand index.
- Gorge Plots: Gorge plots are a graphical tool for visualizing the similarity between consumers and segment representatives. They can be used to assess the separation between segments and to identify consumers who are poorly assigned to their segments. Gorge plots are particularly useful when combined with resampling methods, which allow for the assessment of the stability of the clustering solution.
- Global Stability Analysis: Global stability analysis assesses the reproducibility of a clustering solution across multiple random samples of the data. This can be done by repeatedly drawing bootstrap samples from the original data set and performing clustering on each sample. The similarity between the resulting clustering solutions can then be evaluated using external cluster indices. Global stability analysis can help identify the number of segments that is most robust to random fluctuations in the data.
- Segment Level Stability Analysis: Segment level stability analysis assesses the stability of individual segments within a clustering solution. This can be done by repeatedly drawing bootstrap samples from the original data set and performing clustering on each sample. The stability of each segment can then be evaluated by calculating the Jaccard index between the segment in the original clustering solution and the corresponding

segments in the bootstrap samples. Segment level stability analysis can help identify segments that are consistently identified across multiple random samples of the data.

Implications:

The checklist that we should follow:

- Pre-select the extraction methods that can be used given the properties of our data.
- Use those suitable extraction methods to group consumers.
- Conduct global stability analyses and segment level stability analyses in search of promising segmentation solutions and promising segments.
- Select from all available solutions a set of market segments which seem to be promising in terms of segment-level stability.
- Assess those remaining segments using the knock-out criteria we have defined in Step 2
- Pass on the remaining set of market segments to Step 6 for detailed profiling.

Step 9: Customizing the Marketing Mix

The marketing mix is a set of controllable variables that marketers use to achieve their marketing objectives. The traditional marketing mix consists of four elements: product, price, place, and promotion.

1. **Product:** When customizing the product element of the marketing mix, marketers need to consider the following:

- Product Design: The product itself should be designed to meet the specific needs and wants of the target segment. This may involve modifying an existing product or developing a new product altogether.
- Product Packaging: The product packaging should be designed to appeal to the target segment. This includes the product's shape, size, color, and graphics.
- Product Warranties and After-Sales Support: The product's warranty and after-sales support should be designed to provide the target segment with peace of mind and confidence in the product.

2. **Price:** When customizing the price element of the marketing mix, marketers need to consider the following:

- Price Setting: The price of the product should be set at a level that is acceptable to the target segment. This may involve setting a price that is higher or lower than the prices of competing products.
- Discounts and Promotions: Marketers may offer discounts or promotions to attract new customers or to encourage existing customers to purchase more of the product.

3. **Place:** When customizing the place element of the marketing mix, marketers need to consider the following:
- Distribution Channels: The product should be distributed through channels that are convenient and accessible to the target segment. This may involve selling the product online, in stores, or through a combination of channels.
- Store Location: If the product is sold in stores, the location of the stores should be convenient for the target segment. This may involve opening stores in areas where the target segment lives, works, or shops.

4. **Promotion:** When customizing the promotion element of the marketing mix, marketers need to consider the following:
- Advertising Message: The advertising message should be designed to appeal to the target segment. This includes the message's content, tone, and visuals.
- Media Channels: The advertising message should be delivered through media channels that are used by the target segment. This may involve using traditional media channels such as television and print, or using digital media channels such as social media and online advertising.

Integration with Competition and Positioning: The target segment decision should be integrated with other strategic marketing areas, such as competition and positioning. This ensures that the marketing mix is aligned with the overall marketing strategy.

Implications:
The checklist that we should follow:
- Convene a segmentation team meeting.
- Study the profile and detailed description of the target segment again carefully.
- Determine how the product-related aspects need to be designed or modified to best cater for this target segment.
- Determine how the price-related aspects need to be designed or modified to best cater for this target segment.
- Determine how the place-related aspects need to be designed or modified to best cater for this target segment.
- Determine how the promotion-related aspects need to be designed or modified to best cater for this target segment.
- Review the marketing mix in its entirety.
- If we intend to target more than one segment: repeat the above steps for each of the target segments.
- Ensure that segments are compatible with one another.
- Present an outline of the proposed marketing mix to the advisory committee for discussion and (if required) modification.

Task-1 (b) : Replication of McDonald's Case Study in Python

Team 1

Adarsh Kumar

5th January, 2024

The github link of the replication task is as follows:
https://github.com/theadarshkr/Feynn-Labs-Assignment/blob/main/AdarshKumar_T_1(b).ipynb

The google colab link is as follows:
https://colab.research.google.com/drive/1WYfp0B1DYLns3ahXK1_wThIYXXrAnu_h?usp=sharing