Market Segmentation Review

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Step 1: Deciding Segment

1. **Implications of Committing to Market Segmentation**
    - Commitment to segmentation strategy is crucial for the organization's long-term success.
    - Costs involved include research, surveys, focus groups, designing packages, and creating advertisements.
    - Potential changes may include developing new products, modifying existing ones, adjusting pricing and distribution channels, and refining communication strategies.
    - Strategic business units overseeing segments provide an effective organizational structure.
    - The decision regarding market segmentation strategy should be made at the highest executive level.
    - Continuous communication and reinforcement of the strategy is necessary across all organizational levels and units.

2. **Implementation Barriers**
    - Barriers related to senior management: Resistance or lack of commitment from senior leaders.
    - Barriers related to organizational culture: Resistance to change embedded within the company's culture.
    - Lack of training: Employees may not have the necessary skills or knowledge to implement the strategy effectively.
    - Objective restrictions faced by the organization: Financial constraints limiting the ability to invest in necessary resources, Inability to make structural changes due to various limitations.

Step 2: Specifying the Ideal Target Segment

1. **Segment Evaluation Criteria**
    - The third layer of market segmentation analysis relies heavily on user input.
    - This step involves determining two sets of segment evaluation criteria.
    - The first set is called knock-out criteria: These criteria help eliminate segments that don't meet certain essential requirements.
    - The second set is referred to as attractiveness criteria: These criteria assess the relative attractiveness of the segments that pass the knock-out criteria.
    - The goal is to identify the most promising market segments for further focus and attention.

2. **Knock-Out Criteria**
    - Knock-out criteria decide if market segments are eligible for assessment with attractiveness criteria.
    - Suggested by Kotler, the first set of knock-out criteria includes:
        - Substantiality: Is the segment large enough to be worthwhile?
        - Measurability: Can the segment be accurately measured?
        - Accessibility: Is the segment reachable and reachable efficiently?
    - It's crucial for senior management, the segmentation team, and the advisory committee to understand knock-out criteria.

3. **Attractiveness Criteria**
    - Segmentation teams have the flexibility to choose the most relevant attractiveness criteria for their situation.
    - Attractiveness criteria aren't simply "yes" or "no" assessments.
    - Segments aren't judged solely on whether they meet attractiveness criteria or not.
    - The overall attractiveness across all criteria influences whether a segment is chosen as a target.
    - Selection of target segments occurs in Step 8 of the market segmentation analysis process.

4. **Implementing a Structured Process**
    - The preferred method for assessing market segments as potential target markets is through a segment evaluation plot.
    - Segmentation teams assign values for segment attractiveness and organizational competitiveness.
    - Step 2 of market segmentation analysis doesn't allow completion of the segment evaluation plot since no segments are available for assessment yet.
    - This plot is crucial for comparing different segments and determining their suitability as target markets.

Step 3: Collecting Data

1. **Segmentation Variables**
    - Segmentation variable: It's a characteristic in the data that's used to divide the sample into market segments.
    - Usually, it's just one feature of the consumers in the sample.
    - These variables are essential because they help in identifying existing market segments or creating new ones.
    - They act as the initial step in segmenting the market, making it easier for organizations to target specific groups effectively.

2. **Segmentation Criteria**
    - Segmentation criterion is broader than segmentation variable.
    - Segmentation variable refers to a single measured value, like an item in a survey or an observed expenditure category.

- Segmentation criterion encompasses the nature of information used for market segmentation.
- It can also refer to a specific construct, like benefits sought by customers.
- Here are some of segmentations criteria namely geographic segmentation, Socio-demographic segmentation, Psychographic segmentation, Behavioral segmentation,

Step 5: Extracting Segments

1. **Grouping Consumers**
    - Data driven market segmentation is exploratory by nature.
    - Consumer data are unstructured.
    - The result of market segmentation depends on the structure of the algorithm used.
    - Most of the segmentation methods are from the cluster analysis field.
    - Here clusters correspond to market segments.
    - Algorithms control the market segment.
    - There are two methods of market segmentation namely distance-based methods and model-based methods.

2. **Distance-Based Methods**
    - we use distance as a measure to find similarities or dissimilarities between consumers(observation) in segments.
    - We represent observation(consumers) and Variables in a data matrix form.
    - A distance function is used to calculate the distance between observations and variables.
    - A distance measure has to follow three criteria namely symmetry, the distance of the vector to itself is zero, and triangle inequality.
    - There are three most commonly used distance measures, Euclidean distance, Manhattan or absolute distance, and Asymmetric binary distance.
    - Data needs to be standardized before calculating distance when large number dimensions dominate distance calculation.

2.1 Hierarchical Methods

- Divides a dataset into groups based on similarity.
- This method is suitable for small datasets.
- Divisive Approach starts with the complete dataset and splits it into two segments, then recursively splits each segment further until each observation has its own segment.
- Agglomerative Approach starts with each observation in its own segment and merges the two closest segments step-by-step until the entire dataset forms one segment.
- Both approaches result in a sequence of nested partitions where observations are grouped.
- Linkage method is used to determines how distances between groups are calculated and combined.

- Result of hierarchical clustering, represented as a tree diagram known as dendrogram showing the order in which segments are merged.

2.2 Partitioning Methods

- Partitioning methods in market segmentation involve dividing a dataset into distinct and non-overlapping groups or segments.
- Can be used for large datasets.
- The most popular partitioning method are k-means and k-centroid clustering.
- By using the squared Euclidean distance and computing centroids as the column-wise mean values, the K-means algorithm aims to minimize the within-cluster variance, effectively clustering data points around their respective centroid.
- One of the simplest improvements to the K-means algorithm is to initialize the centroids using "smart" starting values instead of randomly selecting data points from the dataset.

2.3 Hard Competitive Learning

- In hard competitive learning, a consumer is randomly chosen, and their closest segment representative is moved a small step towards the chosen consumer's position.
- This method may find the best overall market segmentation solution, unlike k-means, which can sometimes get stuck in a less optimal solution.

2.4 Neural Gas and Topology Representing Networks

- In the neural gas algorithm, both the closest and the second closest segment representatives (centroids) are adjusted towards the randomly selected consumer, unlike in hard competitive learning where only the closest centroid is adjusted.
- Additionally, topology representing networks keep track of how frequently each pair of centroids is the closest and second closest to a randomly chosen consumer.

2.5 Self-Organising Maps

- In self-organizing maps, segment representatives (centroids) are positioned on a regular grid, typically rectangular or hexagonal in shape.
- The algorithm resembles hard competitive learning: it starts by selecting a random consumer from the dataset.
- The closest representative to this randomly chosen consumer moves a small step in the direction of the consumer.

2.6 Neural Networks

- Auto-encoding neural networks operate differently mathematically compared to traditional cluster analysis methods.
- The most popular method in this family of algorithms involves using a single hidden layer perceptron.
- These networks learn to reconstruct the input data by compressing it into a lower-dimensional representation and then reconstructing it back to its original form.

2.7 Hybrid Approaches

- Some approaches merge hierarchical and partitioning algorithms.
- A major downside of hierarchical clustering is its memory-intensive nature, limiting its application to large datasets.
- Additionally, dendrograms become challenging to interpret with large sample sizes.
- Partitioning clustering suffers from the need to predefine the number of segments, restricting flexibility.

2.8 Two-Step Clustering

- The process involves two main steps.
- First, we run a partitioning procedure, where we group similar data points into clusters using methods like K-means.
- Then, we follow up with a hierarchical procedure, where we further refine the clusters using techniques like hierarchical clustering.
- By combining these two steps, we aim to get more accurate and detailed cluster analysis results.

2.9 Bagged Clustering

- Bagged clustering combines hierarchical and partitioning clustering algorithms with bootstrapping.
- Bootstrapping involves repeatedly sampling from the dataset with replacement, creating multiple bootstrap samples.
- Each bootstrap sample is then used for clustering analysis independently.
- The advantage of bootstrapping is that it reduces the dependence of the final segmentation solution on the exact individuals present in the consumer data.
- By aggregating results from multiple bootstrap samples, bagged clustering aims to improve the robustness and stability of the segmentation solution.

3. Model Based Method

- Model-based methods don't rely on similarities or distances to group consumers into segments.
- Instead, they assume that the true segmentation has two key properties:
- 1) Each segment has a certain size. 2)Consumers in the same segment share specific characteristics.
- These methods don't know the sizes of segments or the characteristics in advance.
- Instead, they use empirical data to determine the best segment sizes and characteristics that match the data.
- By analyzing the data, model-based methods aim to uncover the segment sizes and characteristics that best represent the underlying segmentation of consumers.

3.1 Finite Mixtures of Distribution

- In the simplest case, there are no independent variables (x).
- The model fits a distribution directly to the outcome variable (y).
- This approach focuses solely on understanding the distribution of the outcome variable without considering other variables.

- To compare with distance-based methods, finite mixtures of distributions use similar segmentation variables - various pieces of information about consumers.
- Both methods aim to segment consumers based on certain characteristics, but model-based clustering focuses on fitting distributions to the outcome variable rather than measuring distances between data points.

3.1.1 Normal Distributions

- For metric data, the favored choice is a mixture of several multivariate normal distributions.
- This model is commonly used because it can effectively represent covariance between variables.
- Multivariate normal distributions are versatile and can model complex relationships between multiple variables.
- Additionally, approximations of multivariate normal distributions are commonly observed in both biological and business datasets.

3.1.2 Binary Distributions

- These models are used for binary data, where variables have only two possible outcomes.
- Also known as latent class models or latent class analysis.
- They involve grouping individuals into latent classes or segments based on patterns of binary responses.
- Each latent class is associated with a specific probability distribution of binary outcomes.
- These models are commonly used in fields like psychology, sociology, and marketing to understand underlying latent structures in binary data.

3.2 Finite Mixtures of Regressions

- These models involve a dependent target variable (y) that can be explained by independent variables (x).
- They assume that the relationship between y and x varies across different market segments.
- In other words, the way y is influenced by x differs between segments.
- The model aims to identify and characterize these varying relationships within the data.

3.2.1 Extensions and Variations

- These models can handle various types of data characteristics effectively.
- For metric data, mixtures of normal distributions are commonly used.
- For binary data, mixtures of binary distributions are employed.
- Nominal variables can be modeled using mixtures of multinomial distributions or multinomial logit models.
- For ordinal variables, several models can serve as the basis for mixtures, providing flexibility in modeling ordinal data.

4. Algorithms with Integrated Variable Selection

- Sometimes, the variables used for segmentation may include redundant or noisy information.
- Preprocessing methods help identify and remove these problematic variables.
- One approach is the filtering method, which proposes filtering out irrelevant or noisy variables from the segmentation dataset.
- This ensures that only relevant and informative variables are used for segmentation analysis.

4.1 Biclustering Algorithms

- Biclustering algorithms aim to find subgroups of rows and columns in a dataset that exhibit coherent patterns.
- Biclustering clusters both consumers (rows) and variables (columns) simultaneously.
- Algorithms for blustering work with any type of data, including metric (numeric) and binary (yes/no) data.
- They aim to find groups of consumers that share similar characteristics across certain variables, and vice versa.
- These algorithms are versatile and can identify patterns in various types of datasets, helping to uncover relationships between consumers and variables.

4.2 Variable Selection Procedure for Clustering Binary Data (VSBD)

- VSBD method is based on the k-means algorithm for clustering.
- It assumes that not all variables are necessary for a good clustering outcome.
- Specifically, it assumes the existence of masking variables that may hinder clustering accuracy.
- These masking variables need to be identified and excluded from the set of segmentation variables.
- Removing irrelevant variables aids in identifying the accurate segment structure and makes interpretation easier.

4.3 Variable Reduction: Factor-Cluster Analysis

- Factor-cluster analysis is a two-step process for market segmentation.
- In the first step, segmentation variables undergo factor analysis, which identifies underlying factors or latent variables.
- The original segmentation variables are then discarded.
- In the second step, the factor scores obtained from factor analysis are utilized to create market segments.
- This approach aims to reduce the complexity of the data by identifying underlying factors and using them for segmentation.

5. Data Structure Analysis

- Extracting market segments involves exploration, regardless of the algorithm employed.
- Data structure analysis offers insights into data properties.
- Stability-based data structure analysis is crucial as it indicates the presence of clear, distinct, and well-separated market segments in the data.
- This analysis helps determine if the data naturally divides into recognizable segments or not.

5.1 Cluster Indices

- Cluster indices provide insights into specific aspects of the market segmentation solution.
- The type of insight depends on the cluster index used.
- Two main groups of cluster indices are recognized: internal and external.
- Internal cluster indices are calculated based on a single segmentation solution, utilizing information contained within it.
- External cluster indices require another segmentation as additional input and measure the similarity between two segmentation solutions.

5.2 Gorge Plots

- A straightforward way to evaluate segment separation is by examining the distances from each consumer to all segment representatives.
- Similarity values, indicating how closely a consumer aligns with a segment, can be depicted using gorge plots or silhouette plots.
- Low similarity values suggest that a consumer is distant from the centroid, potentially indicating a poor fit to the segment.
- Conversely, high similarity values suggest a strong likelihood that a consumer belongs to the market segment.

5.3 Global Stability Analysis

- Resampling methods provide an alternative approach for analyzing data structure, applicable to both distance-based and model-based segment extraction techniques.
- These methods assess the stability of a market segmentation solution through repeated calculations.
- Multiple new datasets are generated using resampling methods.
- Segmentation solutions are derived from these datasets, and their stability across repeated calculations is evaluated.
- The most replicable solution, demonstrating consistent stability, is selected as the preferred segmentation solution.

5.4 Segment Level Stability Analysis

- Selecting the best segmentation solution globally doesn't guarantee it contains the optimal individual segment.
- Depending solely on global stability analysis might lead to choosing a solution with overall stability but lacking highly stable segments.
- Emphasizing global stability could result in overlooking the presence of a single, highly stable segment within the solution.

5.4.1 Segment Level Stability Within Solutions (SLSw)

- SLSW focuses on the stability at the segment level.
- Unlike global stability, SLSW calculates stability for each segment individually.
- This allows for the identification of a single highly stable segment, even if other segments within the solution are unstable.
- SLSW enables the detection of potentially attractive niche markets within a segmentation solution.

5.4.2 Segment Level Stability Across Solutions (SLSA)

- SLSA aims to assess how consistently a market segment reoccurs across different segmentation solutions with varying numbers of segments.
- High values of SLSA indicate market segments that naturally emerge from the data, rather than being artificially generated.
- Natural segments, reflected by high SLSA values, are preferred by organizations as they represent genuine patterns in the data.
- These segments require minimal managerial judgment for their identification, as they exist inherently within the data.

GitHub Repo Link: https://github.com/subodhwasekar/Feynn-Labs-Internship