Market Segmentation of McDonald’s

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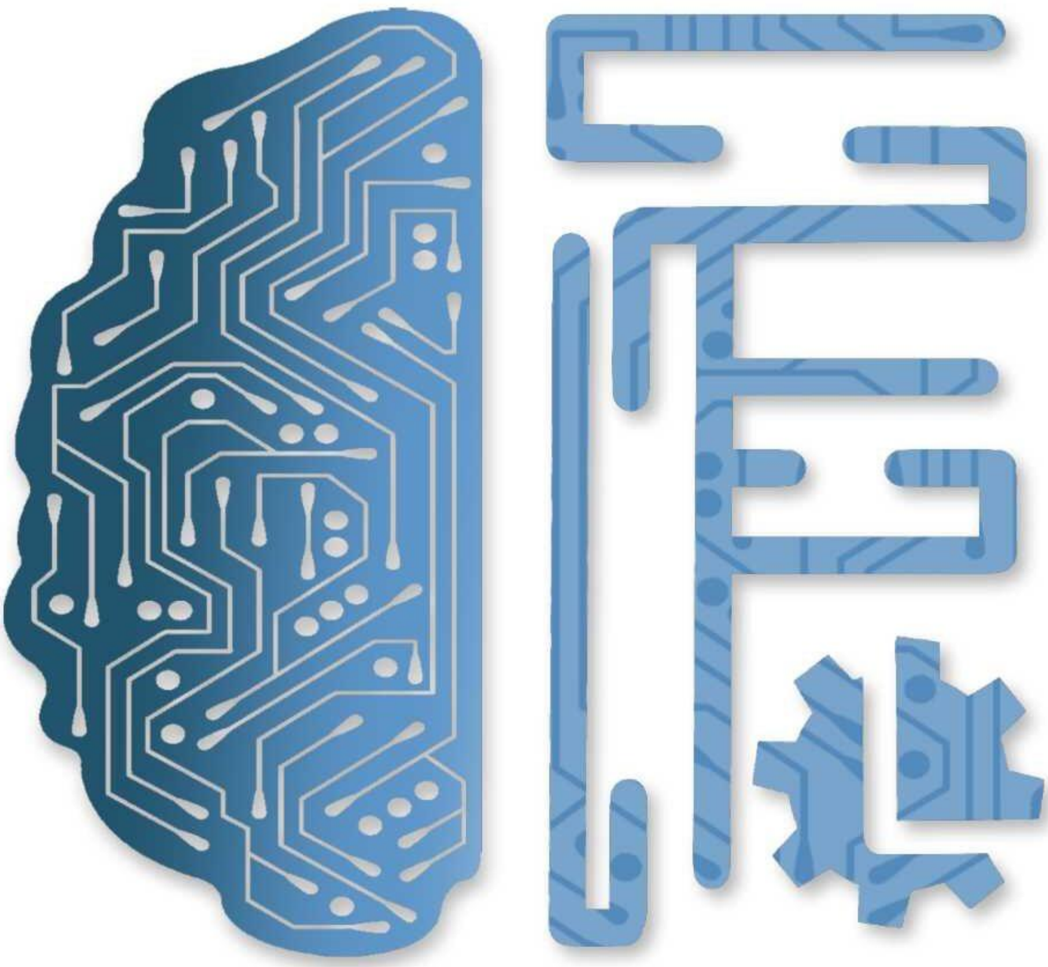

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INTRODUCTION

This document outlines a market segmentation analysis of McDonald's utilizing advanced data techniques. By employing Principal Component Analysis (PCA), K-means clustering, Gaussian Mixture Models (GMM), and regression analysis, we aim to reveal distinct customer segments and their preferences. The study examines crucial factors affecting consumer perceptions and provides actionable insights to refine McDonald’s marketing strategies and product offerings. The objective is to gain a deeper understanding of diverse consumer needs, thereby enhancing McDonald’s market position. Here’s how the general approach to developing and implementing a market segmentation strategy is applied to the McDonald’s case study:

Step 1: Deciding (not) to Segment

Commitment: Organizations must recognize that market segmentation is a long-term commitment that requires the willingness to make substantial changes across the organization. Costs vs. Benefits: It is crucial to evaluate whether the benefits of segmentation, such as increased sales and market share, outweigh the costs associated with research, development, and implementation of different strategies for different segments. Organizational Structure: The organization must be prepared to reorganize around market segments rather than products to maximize the benefits of segmentation. Senior Management Involvement: The decision to pursue market segmentation should be made at the highest level of management and should be communicated clearly across all organizational units. Here, McDonald’s must evaluate whether the benefits of understanding and catering to distinct consumer segments justify the long-term commitment required. This involves assessing the potential for improved customer satisfaction, enhanced brand loyalty, and increased market share against the costs associated with researching and implementing targeted strategies. Adjustments may be needed in product offerings, marketing approaches, and operational structures to effectively serve different customer segments. Additionally, McDonald’s should consider the impact on its organizational structure. This might involve reorganizing business units to focus on specific customer needs, such as healthconscious consumers or those prioritizing convenience and affordability. The decision to pursue such a segmentation strategy should be endorsed by senior management to ensure alignment across the organization and to secure the necessary resources for successful implementation

Step 2: Specifying the Ideal Target Segment

Knock-Out Criteria: Before an organization begins the process of identifying market segments, it is crucial to establish a comprehensive set of essential criteria to guide the segmentation strategy. These criteria are foundational to ensuring that the selected segments are not only viable but also strategically aligned with the organization’s overall goals and capabilities.

First and foremost, **homogeneity** is a critical criterion. Each market segment should consist of consumers who share similar characteristics, behaviors, or needs. This similarity within segments is vital because it allows the organization to create marketing strategies that are highly tailored and relevant to the specific preferences of that group. When segments are homogeneous, the company can more effectively address the unique demands of each group, leading to higher engagement, customer satisfaction, and ultimately, better conversion rates.

Another important criterion is **distinctness**. Segments should be clearly distinguishable from one another, meaning there should be minimal overlap in characteristics between segments. Distinct segments enable the organization to develop specialized marketing messages and offerings that cater specifically to the needs of each group. This distinctness is crucial for maximizing the effectiveness of marketing efforts, as it ensures that each segment receives a unique and targeted approach, reducing the risk of diluting the message or confusing the audience.

Size is also a key consideration in the segmentation process. The segment must be large enough to justify the investment in targeted marketing efforts. While niche segments might have unique characteristics, they must be substantial enough in size to provide a significant return on investment (ROI). A segment that is too small may not generate enough revenue to cover the costs of marketing, making it less viable from a business standpoint. Therefore, assessing the potential size of each segment is essential to ensure that the marketing efforts are both cost-effective and impactful.

In addition to these criteria, segments must align with the organization's strengths. **Alignment with organizational strengths** ensures that the company can effectively meet the needs of the segment, leveraging its existing capabilities, resources, and competitive advantages. By focusing on segments that align with what the organization does best, the company can deliver superior value to those segments, enhancing customer satisfaction and loyalty.

Finally, segments must be **identifiable and reachable**. The organization must be able to clearly identify and define each segment using available data and insights. Moreover, these segments must be reachable through effective communication channels, such as surveys, loyalty programs, or targeted advertising. Ensuring that segments are both identifiable and reachable is essential for executing successful marketing campaigns that engage the target audience and drive results.

By adhering to these knock-out criteria, an organization can ensure that its market segmentation efforts are strategic, targeted, and likely to yield positive outcomes, leading to more effective marketing strategies, stronger customer relationships, and better overall business performance.

Step 3: Collecting Data

Empirical data, used for both commonsense and data-driven market segmentation, identifies or creates market segments and describes them in detail. In commonsense segmentation, a single characteristic, such as gender, splits the sample into segments, while other characteristics describe them. Data-driven segmentation uses multiple variables to find naturally existing segments, like tourists seeking specific vacation benefits. Quality empirical data is crucial for accurate segmentation and description, enabling tailored marketing strategies. Segmentation criteria include geographic, socio-demographic, psychographic, and behavioral factors. Survey data, common in segmentation studies, must be carefully designed to avoid biases and irrelevant variables that hinder accurate segment identification. Market segmentation analysis requires high-quality data to yield accurate results. Responses should be binary or metric to avoid complications with distance measures. Survey data must minimize response biases and styles, ensuring responses reflect true beliefs. A sufficient sample size is crucial; ideally, 100 respondents per segmentation variable. Data should include all necessary and no unnecessary items, with minimal correlation between variables. Ensuring these conditions helps extract meaningful segments and improve the correctness of segment recovery, as demonstrated by studies on sample size and segmentation accuracy.

Step 4: Exploring Data

After collecting data, **Exploratory Data Analysis (EDA)** plays a crucial role in cleaning and pre-processing the data, which in turn guides the selection of appropriate segmentation algorithms. EDA involves a comprehensive examination of the dataset to identify the measurement levels, investigate univariate distributions, and assess dependencies between variables. For example, when working with a travel motives dataset of 1,000 Australians, the process begins with data cleaning, which includes checking for recording errors, ensuring consistent labeling, and re-ordering categorical variables to make them more meaningful. Descriptive analysis then provides numeric summaries and visualizations, such as histograms, boxplots, and bar plots, to give a clear picture of the data's characteristics. These tasks are often facilitated by R commands, which not only streamline the process but also ensure that the analysis is reproducible.

Understanding the data through EDA is essential because it helps avoid misinterpretations and guides the selection of the most suitable segmentation methods. For instance, using finer bins and density estimates in histograms can uncover intricate details in data distribution, such as bi-modal distributions, that might otherwise be overlooked. **Box-and-whisker plots (boxplots)** provide a graphical summary of the data, highlighting the distribution through the five-number summary: minimum, first quartile, median, third quartile, and maximum. Boxplots are particularly useful for handling outliers, as they can limit the length of the whiskers to reduce the impact of extreme values. When dealing with categorical variables, it may be beneficial to merge levels for simplicity or convert them to numeric if appropriate. This ensures that the data is in the best possible form for further analysis.

Standardization of numeric variables is another critical step in EDA, as it balances their influence in subsequent analyses, ensuring that no single variable disproportionately affects the results. Additionally, **Principal Component Analysis (PCA)** is used to reduce data dimensionality by transforming the variables into uncorrelated principal components that are ordered by the amount of variance they explain. PCA is a powerful tool for visualizing data and identifying redundant variables, which can simplify the dataset and make further analysis more efficient. However, it is important to note that PCA should not be used as the sole method for segmentation. Instead, PCA is most valuable when used to explore and understand the underlying structure of the data, aiding in the effective removal of redundant variables and enhancing the overall quality of the segmentation analysis.

By employing EDA, analysts can ensure that the data is well-prepared, understood, and suitable for advanced analysis techniques, leading to more accurate and meaningful insights in segmentation efforts.

Step 5: Extracting Segments

Consumer market segmentation frequently employs clustering methods to group consumers based on similarities. The choice of clustering algorithm plays a crucial role in shaping the segmentation outcomes, as different algorithms have unique strengths and limitations. For instance, **k-means clustering** is effective for forming spherical clusters but struggles with non-spherical shapes like spirals. On the other hand, **single linkage hierarchical clustering** can identify such complex structures but is prone to chain effects, where clusters can become elongated and less meaningful.

Hierarchical clustering builds nested partitions within the data and can be either divisive or agglomerative. This method offers flexibility through various linkage techniques, such as single, complete, and average linkage, each providing different perspectives on the data structure. The choice of **distance measures**—like Euclidean or Manhattan distance—further influences how segments are formed, as they determine the similarity between observations.

When using **hierarchical clustering**, **dendrograms** are vital for visualizing the sequence of nested partitions. However, it's important to note that different software might produce varying dendrograms from the same clustering due to non-unique ordering of leaves and how ties are resolved. For example, when analyzing a **Tourist Risk Taking Dataset** with 563 respondents, hierarchical clustering can be performed using the Manhattan distance matrix. The R commands `dist(risk, method = "manhattan")` and `hclust(risk.dist, method = "complete")` can compute the distance matrix and perform the clustering, respectively. By cutting the dendrogram at a specific height, you can reveal distinct market segments, which can be further analyzed using the `cutree()` function to extract these segments. To understand the profiles of these segments, bar charts can be employed to compare mean values across different risk categories.

Partitioning clustering, particularly **k-means clustering**, is another widely used method. It divides the dataset into *k* segments by iteratively optimizing centroids, making it more suitable for larger datasets due to its efficiency and lower memory requirements compared to hierarchical methods. The k-means algorithm works by specifying the number of segments (*k*), randomly selecting initial centroids, assigning each observation to the nearest centroid, and recomputing the centroids. This process repeats until the algorithm converges. Depending on the distance measure used, centroids are calculated differently—means for squared Euclidean distance and medians for Manhattan distance.

When deciding on the number of clusters, methods like the **scree plot** or **elbow method** are commonly used. These techniques help determine the optimal number of clusters by identifying the point where the reduction in within-cluster distances begins to slow down, indicating diminishing returns in adding more clusters.

An example with **artificial mobile phone data** illustrates how k-means can be used to identify distinct market segments based on features such as price. In R, functions like `cclust()` can extract these clusters, and `cluster hulls()` can visualize them using convex hulls, providing a clear representation of the segments.

To enhance the stability of the k-means clustering results, it's recommended to run the algorithm multiple times with different random initializations. This practice helps identify a more stable solution and ensures that the clustering results are reliable.

In summary, hierarchical clustering is particularly useful for visualizing nested partitions through dendrograms and is best suited for smaller datasets, while k-means clustering is more efficient for larger datasets. Choosing the right clustering method and fine-tuning it through repeated runs and stability analysis are key to achieving meaningful and actionable market segmentation.

Step 6: Profiling Segments

The segmentation analysis is now complete, and the focus shifts to interpreting the results of the four-segment k-means solution. To understand the characteristics of each market segment, a **segment profile plot** is an essential tool. This plot allows for a clear visualization of the key attributes that define each segment and highlights the differences between them. To make the plot easier to interpret, similar attributes should be positioned close to one another, which can be achieved by performing a **hierarchical cluster analysis** on the attributes rather than on the consumers.

For example, in the fast-food dataset, hierarchical clustering helps identify attributes that are most similar, such as "yummy," "tasty," "cheap," "fattening," "convenient," and so on. The resulting order from this analysis is then used to create the segment profile plot. In the plot, the percentage of respondents within each segment who associate certain perceptions with McDonald’s is represented by bars, with the attributes listed on the left side. Marker variables, which are particularly distinct for a segment, are highlighted in color, while others are greyed out. These marker variables stand out either by differing from the overall sample percentage by more than 25 percentage points or by more than 50% in relative terms.

For McDonald’s managers, understanding these segments involves two key tasks: (1) comparing the bars for each segment with the horizontal lines to identify what makes each segment unique compared to the overall consumer market, and (2) comparing the bars across segments to spot the differences between them.

For instance, the plot reveals that Segment 1 perceives McDonald's as "cheap" and "greasy," which is a distinct and negative view. Segment 2 sees McDonald's as "disgusting" and "expensive," clearly setting it apart from other segments. Segment 3 also finds McDonald's "expensive" but associates it with positive attributes like "tasty" and "yummy." Finally, Segment 4 holds a mostly positive view, believing McDonald's is "tasty," "yummy," "cheap," and somewhat "healthy."

Another useful visualization is the **segment separation plot** using **principal components analysis (PCA)**. This plot helps managers grasp how distinct each segment is by projecting the data onto the first two principal components. The centres of the market segments are indicated with black circles containing the segment numbers, and the data points are coloured according to segment membership. This visualization shows that while Segments 1 and 4 both consider McDonald's "cheap," Segment 1 holds a negative view, and Segment 4 has a positive perception. Conversely, Segments 2 and 3 agree that McDonald's is "not cheap," but Segment 2 has a less favourable view compared to Segment 3.

By the end of this step, McDonald's managers should have a solid understanding of the four market segments in terms of the information used to create them. However, further investigation is needed to learn more about the segments beyond this initial analysis. This deeper understanding will be key to tailoring strategies that effectively target each segment.

Step 7: Describing Segments

Describing market segments involves a deeper analysis using additional descriptor variables that were not part of the initial segmentation process. These descriptors, such as demographics and behaviours, provide a more comprehensive understanding of each segment's characteristics, which is crucial for developing targeted marketing strategies. Visualization techniques, like stacked bar charts and mosaic plots, play a key role in interpreting the differences across segments. These methods allow for a clearer insight into the composition of each segment and their associations with variables like gender, income, and environmental attitudes, making it easier to tailor effective marketing strategies.

In segment description, additional descriptor variables are essential for gaining a deeper understanding of market segments. Visualization tools such as mosaic plots and histograms, particularly for variables like moral obligation and age, help reveal differences among segments. For metric variables, parallel box-and-whisker plots effectively illustrate distributions and highlight significant differences, such as those in moral obligation across segments. R packages like lattice and ggplot2 are useful in creating these visualizations. Additionally, the Segment Level Stability Across Solutions (SLSA) plot can track metric variables across different segmentation solutions, aiding in the refinement of marketing strategies by providing deeper insights into segment characteristics and behaviours.

Statistical Tests and Regression Models in Segment Analysis

1. **Pairwise t-Tests and Holm Adjustment**:
    - Pairwise t-tests are used to compare the mean moral obligation scores across different market segments.

    - For example, Segment 1 shows significant differences in mean moral obligation compared to Segments 5 and 6 but not to others.
    - Holm's adjustment controls for multiple testing, reducing the risk of Type I errors.
2. **Tukey's Honest Significant Differences (HSD)**:
    - Tukey's HSD plot is useful for visualizing significant differences between segment pairs.
    - The plot may reveal, for instance, that Segments 5 and 6 have significantly higher moral obligation scores compared to Segments 1-4, while Segments 1-4 do not differ significantly from each other.
3. **Predicting Segment Membership**:
    - **Linear Regression**:
        - This model can show the mean age of respondents in each segment, revealing, for example, that Segment 5 has the youngest average age and Segment 6 the oldest.
    - **Binary Logistic Regression**:
        - This model predicts the probability of being in a specific segment, such as Segment 3, based on variables like age and moral obligation.
        - The analysis might indicate that while age does not significantly impact Segment 3 membership, moral obligation does.
4. **Model Comparison**:
    - Comparing a full model with all descriptors to a stepwise-selected model can reveal the importance of including specific variables, such as moral obligation, for improving model fit.
    - A final model might include variables like Education, NEP (New Environmental Paradigm), and Vacation Behavior for better segment prediction.
5. **Model Performance Visualization**:
    - Visualizing predicted probabilities for segment membership using boxplots can show that a model with selected descriptors (e.g., Education, NEP, Vacation Behavior) provides better separation between segment members and non-members than an initial, more basic model.

Interpretation and Application

- **Segment Differences**:
    - Segments often show significant differences in key variables like moral obligation. For instance, Segments 5 and 6 might display a higher sense of responsibility compared to others.
    - Tukey's HSD plot can confirm these distinctions, highlighting the uniqueness of Segments 5 and 6 from Segments 1-4 in terms of moral obligation.
- **Age and Moral Obligation**:
    - While age alone may not significantly impact segment membership, moral obligation often emerges as a critical factor, with higher scores correlating with a greater likelihood of belonging to a particular segment, such as Segment 3.
- **Model Selection**:
    - The stepwise-selected model, including variables like Education, NEP, and Vacation Behavior, typically offers more accurate predictions of segment

membership than models that rely solely on basic variables like age and moral obligation.

This analysis highlights the importance of using statistical tests and regression models to understand market segments and their characteristics. By carefully selecting and analyzing appropriate variables, and applying model adjustment techniques, businesses can make more accurate predictions and develop more effective, targeted marketing strategies.

In the context of decision trees, the analysis might reveal that splits are based on variables like moral obligation and education. Consumers with lower levels of these variables could be assigned to certain segments, while those with higher levels might belong to others. Terminal nodes in the decision tree would show varying segment memberships, and some nodes might predict incorrect segment membership for many respondents, indicating areas where the model could be improved.

Step 8: Selecting the Target Segment(s)

In market segmentation is where a company decides which market segment(s) to target. This decision is crucial as it significantly impacts the company's future. After identifying potential segments and profiling them, the company evaluates each segment's attractiveness and its own competitiveness in serving that segment. To help with this decision, companies often use decision matrices, which plot segment attractiveness against organizational competitiveness. This is like assessing how desirable a segment is and how well the company can serve it. For example, segment attractiveness might include factors like market size, while organizational competitiveness could consider the company's ability to meet the segment's needs. The process involves assigning weights to different attractiveness criteria and scoring each segment. These scores are then plotted on a matrix to visualize which segments are most promising. The company then selects the target segment(s) based on this evaluation, ensuring they choose segments where they can compete effectively and offer value. This strategic targeting is essential for developing tailored marketing strategies and achieving long-term success.

Step 9: Customising the Marketing Mix

In Step 9, the marketing mix is tailored to target a specific market segment. For instance, if McDonald's managers decide to focus on Segment 3—young customers who enjoy McDonald's food, find it tasty, but consider it expensive—they might introduce a "MCSUPERBUDGET" line. This new product line would be designed to meet the price expectations of Segment 3 (4Ps: Price), potentially fostering loyalty among these customers. As they earn more, these customers might transition to McDonald's regular product range, where price becomes less of a concern.

To avoid cannibalizing their main product line, McDonald's would need to ensure that the MCSUPERBUDGET products are distinctly different in features (4Ps: Product). The communication strategy would involve identifying and utilizing channels that are popular with Segment 3 to promote the new line (4Ps: Promotion). While the distribution would remain the same, with all food sold in McDonald's outlets (4Ps: Place), management could consider implementing a separate MCSUPERBUDGET lane. This lane might have slightly longer wait times, which could further prevent cannibalization of the main product line.

References

• Dolnicar, S., Grün, B., & Leisch, F. (2018). Market Segmentation Analysis: Understanding It, Doing It, and Making It Useful. Springer Nature Singapore Pte Ltd.

https://link.springer.com/book/10.1007/978-981-10-8818-6

Github Links

Asna: https://github.com/ASNAJAMS/Market-Segmentation

Anjali: https://github.com/anjali202377/Mc-Donald-s-Market-Segmentation-Analysis

Nirmal : https://github.com/NirmalKoshy/Market-Segmentation-Case-Study-

Harsh : https://github.com/harshsinghrana/Market-Segmentation-of-MacD