MARKET SEGMENTATION

Team Members

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INTRODUCTION

The purpose of marketing is to match the genuine needs and desires of consumers with the offers of suppliers particularly suited to satisfy those needs and desires. This matching process benefits consumers and suppliers, and drives an organisation's marketing planning processes.

Strategic marketing planning is important because it determines the long-term direction of an organization. It involves identifying consumer needs and desires, strengths and weaknesses internal to the organization, and external opportunities and threats that the organization may face. Through a SWOT analysis, an organization can identify its strengths, weaknesses, opportunities, and threats, which can help in developing the strategic marketing plan.

Once the strategic marketing plan has been established, decisions can be made about which consumers to focus on (segmentation and targeting), and which image of the organization to create in the market (positioning). These decisions are critical because they determine the long-term direction of the organization, and cannot easily be reversed. Only when these decisions have been made can work on the tactical marketing plan begin.

The tactical marketing plan involves developing and modifying the product to meet the needs and desires of the target segment, determining the price in view of cost, competition, and the willingness to pay of the target segment, selecting the most suitable distribution channels to reach the target segment, and communicating and promoting the offer in a way that is most appealing to the target segment. The tactical marketing plan depends entirely on the strategic marketing plan, but the strategic marketing plan does not depend on the tactical marketing plan.

Benefits of market segmentation:

- Allows organizations to tailor their marketing efforts to specific groups of consumers, which can lead to increased efficiency and effectiveness of marketing campaigns.
- Helps organizations identify and understand the unique needs and desires of different consumer groups, allowing them to develop products and services that better meet those needs.
- Can lead to increased customer loyalty and satisfaction, as consumers feel that their specific needs are being met.
- Enables organizations to more accurately measure the success of their marketing efforts by tracking the response of specific consumer groups.

Costs of market segmentation:

- Can be expensive and time-consuming to conduct the research necessary to identify and understand different consumer segments.
- Can lead to increased complexity in marketing efforts, as organizations need to develop different marketing strategies and campaigns for each segment.
- May lead to increased competition within specific segments as organizations compete for the attention and loyalty of consumers within those segments.

Variables of market segmentation:

- Demographic segmentation: dividing consumers into groups based on characteristics such as age, gender, income, education, and occupation.
- Psychographic segmentation: dividing consumers into groups based on personality traits, values, attitudes, and interests.
- Behavioural segmentation: dividing consumers into groups based on their behaviour and how they interact with products or services.
- Geographic segmentation: dividing consumers into groups based on their geographic location.

Segmentation based on the choice of Segmentation variables:

Variable	Dimensions	Sample survey questions
Age	Unidimensional	How old are you?
Gender	Unidimensional	What is your gender identity?
Country of Origin	Unidimensional	Where do you live?
Prior Purchase	Unidimensional	Have you purchased our service before?
Benefits sought	Multidimensional	When booking flights online, do you care about • Convenience • Value for money • Speed • Ability to compare fares
Motives	Multidimensional	When choosing a vacation, do you • Rest and relax • Explore new things • Meet new people • Learn about other cultures • Getaway from everyday routine

Data driven Market segmentation approach:

	Common sense/ Common sense segmentation	Common sense/ data driven segmentation	Data driven/ Common sense segmentation	Data driven/ data driven segmentation
Primary segmentation variables	Commonsense e.g. age, country of origin	Commonsense e.g. age, country of origin	Data driven e.g.expenditure, vacation activities	Data driven e.g. travel motives, expenditures
Secondary segmentation variables	Commonsense e.g. gender, seeking adventure or not	Data driven e.g. travel motives, vacation activities	Commonsense e.g. Gender. Family status	Data driven e.g. vacation activities, information sources used
Example	Young female tourists	Mature aged who play golf, enjoy wine-tastings and fine-dining	Tourists who engage in many activities that attract entrance fee like theme park, zoo	Tourists who want to learn about the culture and local people, who attend local cultural events and food festivals

Market Segmentation Analysis Step by step:

Market segmentation analysis can be carried out using a ten-step approach as shown in below figure. The approach applies to both common sense and data-driven segmentation strategies. The initial step involves evaluating the benefits and drawbacks of pursuing a segmentation strategy and deciding whether to proceed. The organization then specifies the ideal market segment characteristics before collecting empirical data. The data is explored before market segments are extracted, profiled, and described in detail. The organization then selects one or a few segments to target, develops a customized marketing mix, and evaluates the success of the strategy upon completion. It is crucial to continuously monitor the segments for possible changes in size or characteristics that may require modifications to the segmentation strategy.


Commonsense segmentation
Data-driven segmentation
STEP 1 - Deciding (not) to segment
Is the market suitable?
Can you make a long-term commitment?
Is the market suitable?
Can you make a long-term commitment?
STEP 2 - Specifying the ideal target segment
What would your ideal target segment look like?
What would your ideal target segment look like?
STEP 3 - Collecting data
Collect data
(segmentation variable and descriptor variables)
Collect data
(segmentation and descriptor variables)
STEP 4 - Exploring data
Explore data, pre-process if required.
Explore data, pre-process if required.
STEP 5 - Extracting segments
Split consumers into segments
using the segmentation variable.
Use distance-based, model-based
or hybrid algorithms.
STEP 6 - Profiling segments
Determine key features
of the extracted market segments.
STEP 7 - Describing segments
Describe segments in detail.
Describe segments in detail.
STEP 8 - Selecting (the) target segment(s)
Evaluate segments and select target segment(s).
Evaluate segments and select target segment(s).
STEP 9 - Customising the marketing mix
Develop a customised marketing mix.
Develop a customised marketing mix.
STEP 10 - Evaluation and monitoring
Evaluate success, monitor changes.
Evaluate success, monitor changes.

STEP-1: Deciding (not) to Segment:

The key implication of pursuing a market segmentation strategy is that the organization must commit to the segmentation strategy on the long term. This commitment includes the willingness and ability of the organization to make substantial changes and investments, such as developing new products, modifying existing products, changes in pricing and distribution channels, and communication with the market. These changes may also influence the internal structure of the organization, which may need to be adjusted, for example, to target different market segments. The decision to investigate the potential of a market segmentation strategy must be made at the highest executive level, systematically and continuously communicated, and reinforced across all organizational units.

There are several potential barriers to successful implementation of a market segmentation strategy. The first group of barriers relates to senior management, including lack of leadership, pro-active championing, commitment, and involvement in the market segmentation process. A lack of resources, either for the initial market segmentation analysis or for the long-term implementation of a market segmentation strategy, can also impede the success of market segmentation.

A second group of barriers relates to organizational culture, including a lack of market or consumer orientation, resistance to change, lack of creative thinking, poor communication, lack of sharing of information and insights across organizational units, short-term thinking, unwillingness to make changes, and office politics. Lack of training and a formal marketing function or qualified marketing expert in the organization, and lack of a qualified data manager and analyst, can also represent major stumbling blocks.

Objective restrictions faced by the organization, such as lack of financial resources or the inability to make the required structural changes, can also be obstacles. Process-related barriers include not having clarified the objectives of the market segmentation exercise, lack of planning or bad planning, lack of structured processes to guide the team through all steps of the market segmentation process, a lack of allocation of responsibilities, and time pressure.

STEP-2: Specifying the Ideal Target segment:

This step involves determining two sets of segment evaluation criteria, namely knock-out criteria and attractiveness criteria. Knock-out criteria are non-negotiable features that the organization would consider targeting, while attractiveness criteria are used to evaluate the relative attractiveness of the remaining market segments in compliance with the knock-out criteria. User input is crucial in this step, and the organization must commit to contributing to the market segmentation analysis process by conceptualizing the evaluation criteria. There is a wide array of proposed criteria in the literature, such as measurable, substantial, accessible, sufficiently different, large enough, growing, competitively advantageous, profitable, sensitive to price, socio-political considerations, and others. The literature does not generally distinguish between knock-out and attractiveness criteria.

- Knockout Criteria:
  Knock-out criteria are used to determine if market segments are suitable for further assessment using segment attractiveness criteria. The article outlines the various criteria recommended by experts in the field, including substantiality, measurability, accessibility, homogeneity, distinctiveness, size, and matching with organizational strengths. It is crucial for senior management, the segmentation team, and the advisory committee to understand these criteria. The article emphasizes the need for specifying the minimum viable target segment size.
  To ensure that market segments resulting from market segmentation analysis are worth pursuing, knock-out criteria are used to determine their suitability for assessment using segment attractiveness criteria. The original criteria suggested by Kotler in 1994 include substantiality, measurability, and accessibility, but additional criteria have been recommended by other authors. These criteria include homogeneity, distinctiveness, size, matching the organization's strengths, identifiability, and reachability. Knock-out criteria must be understood by senior management, the segmentation team, and the advisory committee. While some criteria require no further specification, others, such as the minimum viable target segment size, must be specified. By using these knock-out criteria, organizations can identify and focus on market segments that offer the greatest potential for success.

- Attractiveness Criteria:
  Attractiveness criteria are used to evaluate the relative attractiveness of the remaining market segments after the knock-out criteria have been applied. These criteria are used to select one or more target segments from the remaining options. Attractiveness criteria can be based on a wide range of factors, including market size, growth potential, profitability, competition, and fit with the company's resources and capabilities.
  Attractiveness criteria should be based on the company's strategic priorities and objectives. They should also be flexible enough to allow for changes in the market and the company's resources and capabilities. For example, a company that is experiencing strong growth in a particular market may prioritize growth potential as an attractiveness criterion, while a company that is focused on maximizing profitability may prioritize profitability as an attractiveness criterion.

- Once the knock-out and attractiveness criteria have been established, they can be used to evaluate potential market segments. This involves gathering data on each segment, analysing the data using the established criteria, and selecting one or more target segments that meet the criteria.

<u>STEP-3: Collecting the data:</u>

<u>Segmentation criteria based on variables</u>

- Demographic variables: These variables are based on characteristics such as age, gender, income, education, family size, ethnicity, and occupation. For example, a company may target young adults aged 18-25 for a new energy drink product.

- Geographic variables: These variables are based on geographic location and include region, city size, climate, and population density. For example, a ski equipment manufacturer may target customers in regions with colder climates and mountainous terrain.
- Psychographic variables: These variables are based on consumer lifestyle, values, interests, and personality traits. For example, a company may target environmentally-conscious consumers who are interested in sustainable products.
- Behavioural variables: These variables are based on consumer behaviour, including purchasing patterns, brand loyalty, product usage, and attitudes toward the product or service. For example, a company may target frequent users of a particular product or brand.

Data from Survey studies

Survey data is cheap and easy to collect, making it a feasible approach for any organisation. Few key aspects need to be considered when using survey data

- Choice of variables:
  selecting the variables that are included as segmentation variable in com- monsense segmentation, or as segmentation variables in data-driven segmentation, is critical to the quality of the market segmentation solution
- Response options
  Answer options provided to respondents in surveys determine the scale of the data available for subsequent analyses. Options allowing respondents to indicate a number, such as age or nights stayed at a hotel, generate metric data. Metric data allow any statistical procedure to be performed and are therefore well suited for segmentation analysis
- Response styles
  Survey data is prone to capturing biases. A response bias is a systematic tendency to respond to a range of questionnaire items on some basis other than the specific item content. some respondents displaying an acquiescence bias (a tendency to agree with all questions) could result in one market segment having much higher than average agreement with all answers. Such a segment could be misinterpreted

- Sample size
  increasing the sample size improves the correctness of the extracted segments. Interestingly, however, the biggest improvement is achieved by increasing very small samples. As the sample size increases, the marginal benefit of further increasing the sample size decreases.

Data from Internal sources

Businesses can collect data from their own customer database, sales data, and customer service interactions to gain insights into customer needs, behaviours, and preferences. Typical examples are scanner data available to grocery stores, booking data available through airline loyalty programs, and online purchase data. The strength of such data lies in the fact that they represent actual behaviour of consumers

Data from experimental studies

Experimental data can result from field or laboratory experiments. For example, they can be the result of tests how people respond to certain advertisements. The response to the advertisement could then be used as a segmentation criterion. Experimental data can also result from choice experiments or conjoint analyses. One such method is A/B testing where certain features are tested on control groups.

STEP-4: Exploring data:

This step can be further broken down to smaller steps. Data cleaning is a crucial step in the data analysis process that involves identifying and correcting or removing errors, inconsistencies, and inaccuracies in the data.

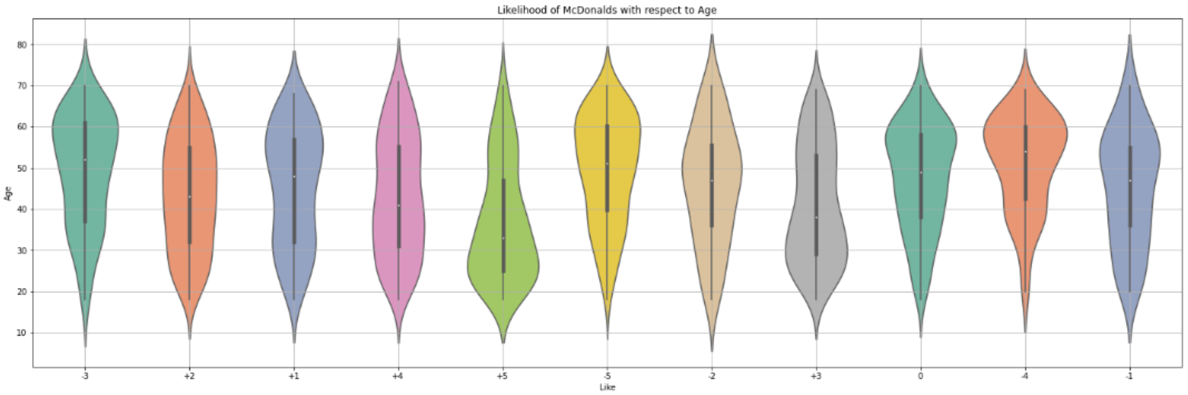
- Data Cleaning
  - Handling missing values:
    decide on a strategy for handling missing values, such as imputation (replacing missing values with estimates) or deletion (removing rows or columns with missing values).
  - Handling duplicate values:
    identify and remove duplicates from the dataset to avoid biasing the analysis.
  - Data transformation:
    This step involves converting the data into a suitable format for analysis. It may include converting categorical data into numeric data, scaling or standardizing the data, and creating new variables or features.
  - Handling outliers:
    Outliers are extreme values that can skew the analysis. You need to identify and handle outliers using methods such as winsorizing, trimming, or removing outliers.
  - Data integration:
    This step involves combining multiple datasets into a single dataset for analysis. It may include merging data from different sources or databases.

```
#Customer segmentation - based on pyschographic segmentation

#For convenience renaming the category
# Replace the values in the 'Like' column
df['Like'] = df['Like'].replace({'I hate it!-5': '-5', 'I love it!+5': '+5'})

# Create a violin plot
sns.violinplot(x='Like', y='Age', data=df, palette='Set2')
plt.grid(True)
# Set the plot title
plt.title('Likelihood of McDonalds with respect to Age')

# Show the plot
plt.show()
```



- D

```python
#Label encoding for categorical - Converting 11 cols with yes/no

from sklearn.preprocessing import LabelEncoder
def labelling(x):
    df[x] = LabelEncoder().fit_transform(df[x])
    return df

cat = ['yummy', 'convenient', 'spicy', 'fattening', 'greasy', 'fast', 'cheap',
       'tasty', 'expensive', 'healthy', 'disgusting']

for i in cat:
    labelling(i)
df.head()
```

	yummy	convenient	spicy	fattening	greasy	fast	cheap	tasty	expensive	healthy	disgusting	Like	Age	VisitFrequency	Gender
0	0	1	0	1	0	1	1	0	1	0	0	-3	61	Every three months	Female
1	1	1	0	1	1	1	1	1	1	0	0	+2	51	Every three months	Female
2	0	1	1	1	1	1	0	1	1	1	0	+1	62	Every three months	Female
3	1	1	0	1	1	1	1	1	0	0	1	+4	69	Once a week	Female
4	0	1	0	1	1	1	1	0	0	1	0	+2	49	Once a month	Male

```python
#Histogram of the each attributes
plt.rcParams['figure.figsize'] = (16,14)
df.hist(color='teal')
plt.show()
```

This involves summarizing the key features of the dataset, such as the mean, median, mode, range, standard deviation, and variance.

- Data visualization:
  This step involves creating graphical representations of the data to identify patterns, trends, and anomalies. Examples of visualization techniques include scatter plots, histograms, box plots, and heat maps.

- Pre-processing
  - Categorical variables:
    For some analyses, it is necessary to convert continuous numerical data into categorical data by creating equally sized intervals as category. For example, age. There are other methods such as label encoding, one hot encoding, and dummy encoding which can be used to transform the select features into categorical variables.
  - Numerical 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.

- Principal Components Analysis
  PCA (Principal Component Analysis) is a popular technique used for dimensionality reduction and feature extraction from high-dimensional datasets. It is a mathematical algorithm that transforms a set of correlated variables into a new set of uncorrelated variables, called principal components. The steps involved in PCA are:
  - Standardization:
    The data is standardized by subtracting the mean and dividing by the standard deviation to ensure that all variables are on the same scale.
  - Calculation of Covariance Matrix:
    The covariance matrix is computed for the standardized dataset. The covariance matrix is a square matrix that contains the covariances between all pairs of variables in the dataset.
  - Eigenvector Decomposition:
    The eigenvectors and eigenvalues of the covariance matrix are computed. The eigenvectors are the directions in which the data varies the most, while the eigenvalues represent the amount of variation explained by each eigenvector.
  - Selection of Principal Components:
    The principal components are selected based on the eigenvalues. The first principal component is the eigenvector that explains the most variation in the dataset, the second principal component is the eigenvector that explains the most variation remaining after the first principal component has been removed, and so on.
  - Projection of Data:
    The data is projected onto the new set of variables, or principal components, to obtain a reduced dimensional representation of the original dataset.

```
#Principal component analysis

from sklearn.decomposition import PCA
from sklearn import preprocessing

pca_data = preprocessing.scale(x)

pca = PCA(n_components=11)
pc = pca.fit_transform(x)
names = ['PC1','PC2','PC3','PC4','PC5','PC6','PC7','PC8','PC9','PC10','PC11']
pf = pd.DataFrame(data = pc, columns = names)
round(pf,3)
```

	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11
0	0.425	-0.219	0.663	-0.401	0.202	-0.390	-0.212	0.163	0.181	0.516	-0.567
1	-0.219	0.388	-0.731	-0.095	0.045	-0.087	-0.096	-0.035	0.111	0.493	-0.500
2	0.375	0.730	-0.122	0.692	0.840	-0.687	0.583	0.364	-0.322	0.062	0.243
3	-0.173	-0.353	-0.844	0.207	-0.681	-0.036	-0.054	-0.231	-0.028	-0.251	-0.051
4	0.187	-0.808	0.029	0.548	0.854	-0.097	-0.457	0.172	-0.074	0.032	0.082
...	...	...	...	...	...	...	...	...	...	...	...
1448	1.550	0.275	-0.014	0.201	-0.145	0.307	-0.075	0.346	-0.137	-0.433	-0.456
1449	-0.957	0.014	0.304	0.444	-0.134	0.382	-0.326	0.878	-0.304	-0.247	-0.194
1450	-0.186	1.063	0.221	-0.468	-0.188	-0.193	-0.092	-0.037	0.038	0.057	-0.013
1451	-1.182	-0.039	0.562	0.701	0.048	0.194	-0.027	-0.339	0.022	-0.003	-0.105
1452	1.550	0.275	-0.014	0.201	-0.145	0.307	-0.075	0.346	-0.137	-0.433	-0.456

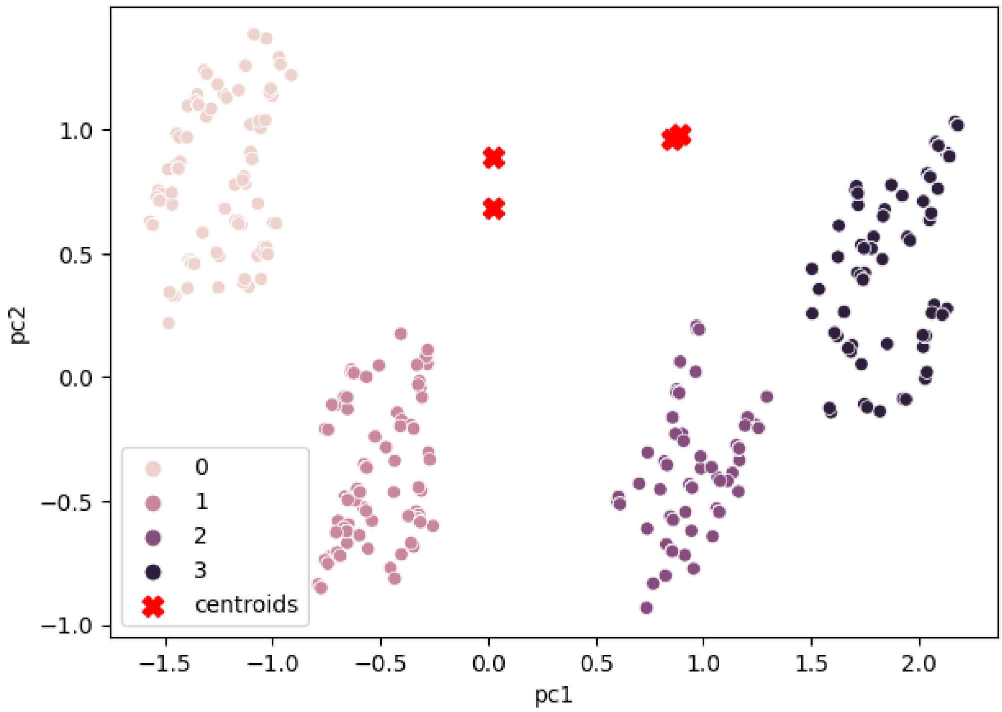
Step 5: Extracting Segments
extraction techniques, we subdivide this step into three sections.
In the first section, we will use standard k-means analysis.
In the second section, we will use finite mixtures of binary distributions.
In the third section, we will use finite mixtures of regressions.

First section: we will use standard k-means analysis
K-means analysis is a commonly used unsupervised machine learning algorithm used to group data points into K number of clusters based on their similarity. In a standard K-means analysis, the algorithm works as follows:

- The number of clusters (K) is specified.
- The initial centroid for each cluster is randomly selected.
- Each data point is assigned to the closest centroid, based on the Euclidean distance between the point and the centroid.
- The centroid of each cluster is updated to the mean of all the points assigned to that cluster.
- Steps 3 and 4 are repeated iteratively until convergence, which is defined as no further changes in the assignment of data points to clusters or the centroids.
- The final result is K clusters, where each data point belongs to the cluster with the closest centroid.

- K-means analysis is widely used in various fields, including image processing, marketing, and customer segmentation, to name a few. However, it should be noted that K-means analysis is sensitive to the initial centroid selection, and the quality of the results can depend on the choice of K and the data being analyzed.

```
#Visulazing clusters
sns.scatterplot(data=pf, x="pc1", y="pc2", hue=kmeans.labels_)
plt.scatter(kmeans.cluster_centers_[:,0], kmeans.cluster_centers_[:,1],
            marker="X", c="r", s=80, label="centroids")
plt.legend()
plt.show()
```



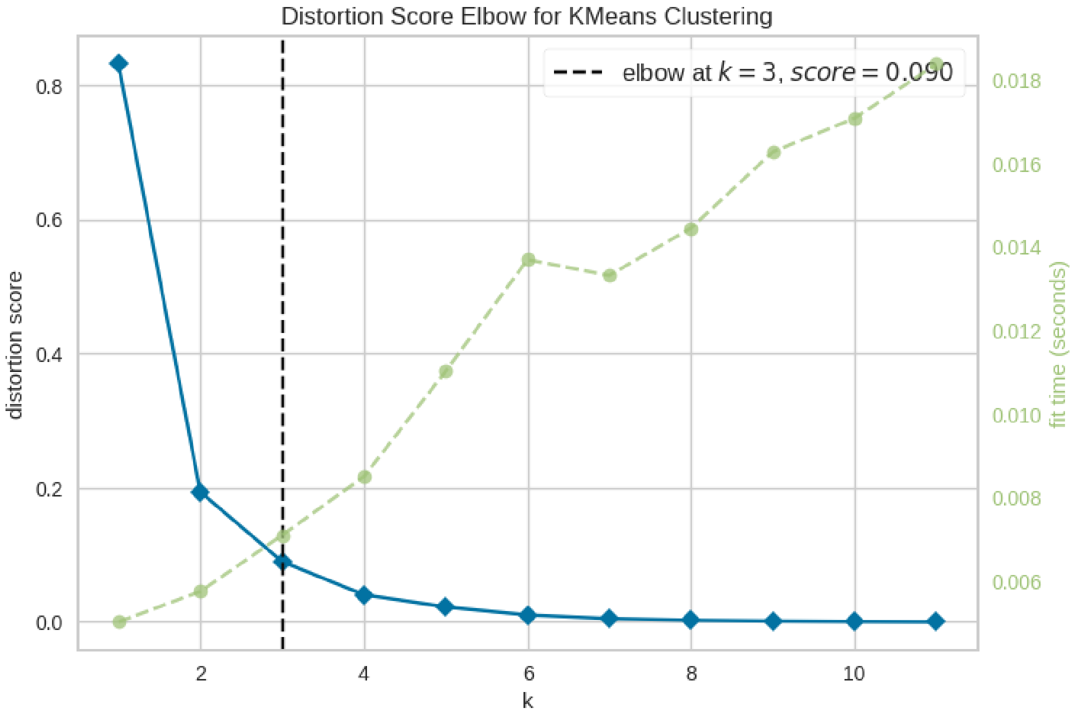
Second Section: we will use finite mixtures of binary distributions.
Finite mixtures of binary distributions are a statistical method used to model data that are binary in nature (i.e., have only two possible outcomes, such as success or failure, 0 or 1, yes or no, etc.). A mixture model assumes that the observed data come from a combination of underlying subpopulations, each with its own distribution. In the case of binary data, a mixture model assumes that there are multiple underlying distributions that generate the observed data, and each distribution represents a different subpopulation of the data.

A finite mixture of binary distributions is a mixture model that assumes that the underlying distributions are all binary distributions, such as the Bernoulli distribution or the Binomial distribution. The model specifies the number of subpopulations and their associated probabilities, as well as the parameters of the binary distributions (e.g., success probabilities).

Finite mixtures of binary distributions can be used for a variety of applications, such as clustering, classification, and density estimation. They are particularly useful when the observed data are not easily explained by a single binary distribution, but instead may be better explained by a combination of distributions. By modeling the data as a mixture of distributions, we can better understand the underlying structure of the data and make more accurate predictions or classifications.

```
#Extracting segments

#Using k-means clustering analysis
from sklearn.cluster import KMeans
from yellowbrick.cluster import KElbowVisualizer
model = KMeans()
visualizer = KElbowVisualizer(model, k=(1,12)).fit(new_df)
visualizer.show()
```



Third Section: **we will use finite mixtures of regressions.**

Finite mixtures of regressions is a statistical method used to model data where the relationship between the dependent variable and the independent variables may vary across subpopulations. The method assumes that the observed data are a mixture of several subpopulations, each with its own regression equation. In other words, the model specifies that the data are generated by multiple regression equations, each associated with a different subpopulation, and each with its own set of coefficients.

In a finite mixture of regressions, the mixture model assumes that the subpopulations are characterized by different means, variances, and/or correlation structures. The model specifies the number of subpopulations and their associated probabilities, as well as the parameters of the regression equations (e.g., coefficients). The parameters of the subpopulations and the regression equations are estimated from the data using maximum likelihood estimation.

Finite mixtures of regressions can be used in a variety of applications, such as clustering, classification, and prediction. They are particularly useful when the relationship between the dependent variable and the independent variables is not consistent across the entire sample, but instead may vary across different subgroups of the data. By modeling the data as a mixture of regressions, we can identify these subgroups and better understand the underlying structure of the data.

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Finite mixtures of binary distributions can be used for a variety of applications, such as clustering, classification, and density estimation. They are particularly useful when the observed data are not easily explained by a single binary distribution, but instead may be better explained by a combination of distributions. By modeling the data as a mixture of distributions, we can better understand the underlying structure of the data and make more accurate predictions or classifications.

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Step 6: Profiling Segments:

Profiling is necessary for data-driven market segmentation to identify the defining characteristics of resulting market segments. Good profiling is essential for correctly interpreting segmentation results, which are often difficult for managers to crack. Graphical statistics approaches can make profiling less tedious and less prone to misinterpretation.

The Australian vacation motives dataset was used to extract segments using neural gas clustering. Data-driven segmentation solutions are often presented as oversimplified summaries or large, hard-to-interpret tables. Table 8.1 shows the mean values of segmentation variables by segment, requiring a large number of comparisons to understand segment characteristics. Comparing multiple segmentation solutions would be even more tedious. Providing information about statistical significance is not appropriate due to the nature of segment creation.

The next section discusses the importance of visualisations in market segmentation analysis. While tabular representations are typically used to present market segmentation solutions, graphics and data visualisation play an integral part in statistical data analysis. Visualisations are particularly useful in exploratory statistical analysis, as they provide insights into complex relationships between variables. Visualisations offer a simple way of monitoring developments over time, making them especially useful in times of big data.

Market segmentation analysts recommend using visualisation techniques to make the results of a market segmentation analysis easier to interpret. Statistical graphs facilitate the interpretation of segment profiles and make it easier to assess the usefulness of a market segmentation solution.

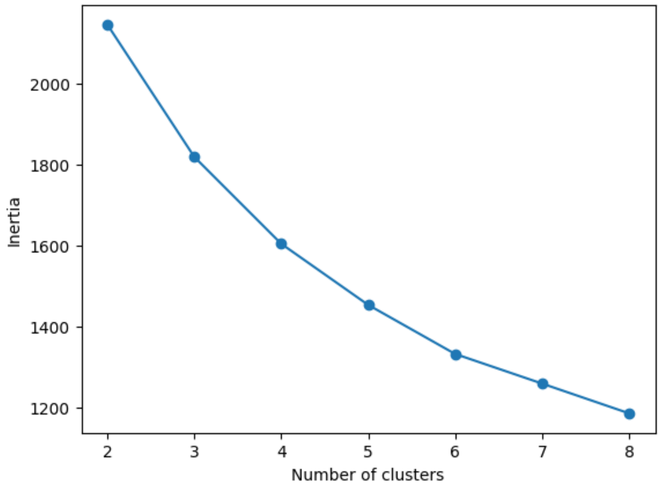
Visualising segmentation variables in a meaningful order can improve the clarity of the visualisation. One way to understand the defining characteristics of each market segment is to produce a segment profile plot. The segment profile plot shows how each market segment differs from the overall sample for all segmentation variables. Clustering the columns of the data matrix can order segmentation variables by the similarity of answer patterns.

A segment profile plot is a panel plot representing one segment. The dots in the story represent the total mean values for the segmentation variables across all observations in the data set. Marker variables, particularly characteristic of a segment, are identified and depicted in colour. Other segmentation variables are greyed out. The definition of marker variables used in the segment profile plot is suitable for binary variables, considering the absolute and relative difference of the segment mean to the total mean.

```
np.random.seed(1234)

# Perform k-means clustering for k = 2 to 8
inertias = []
for k in range(2, 9):
    km28 = KMeans(n_clusters=k, n_init=10, verbose=0)
    km28.fit(md)
    inertias.append(km28.inertia_)

# Find the elbow point
import matplotlib.pyplot as plt
plt.plot(range(2, 9), inertias, marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
plt.show()
```



The above plot does not show a clear elbow that would indicate a good number of market segments to extract. The sum of distances within market segmei decreases slowly as the number of segments increases, but there is no point where the drop in the sum of distances is significant. This makes it difficult t determine a suitable number of segments using this approach.

Another method to identify a good number of segments is stability-based data structure analysis. This approach assesses the stability of segmentation solutions across repeated calculations and determines whether the market segments occur naturally in the data or if they have to be artificially constructe Using an unstable, random solution for market segmentation would provide little confidence to McDonald's management for investing resources in a mark segmentation strategy. Therefore, assessing the stability of segmentation solutions across repeated calculations ensures that only stable solutions are us for market segmentation.

Step 7: Describing Segments:

After collecting and analyzing data, the next step in the market segmentation process is to describe the target segments in detail. This involves developing a profile of each segment that includes demographic, psychographic, and behavioral characteristics

Each segment may also have unique behavioral characteristics, such as the frequency of their visits to McDonald's, their preferred menu items, and their willingness to try new menu offerings.

By developing a detailed profile of each target segment, McDonald's can tailor their products, services, and marketing efforts to meet the specific needs and preferences of each group. This can help to increase customer loyalty and drive growth and profitability for the company

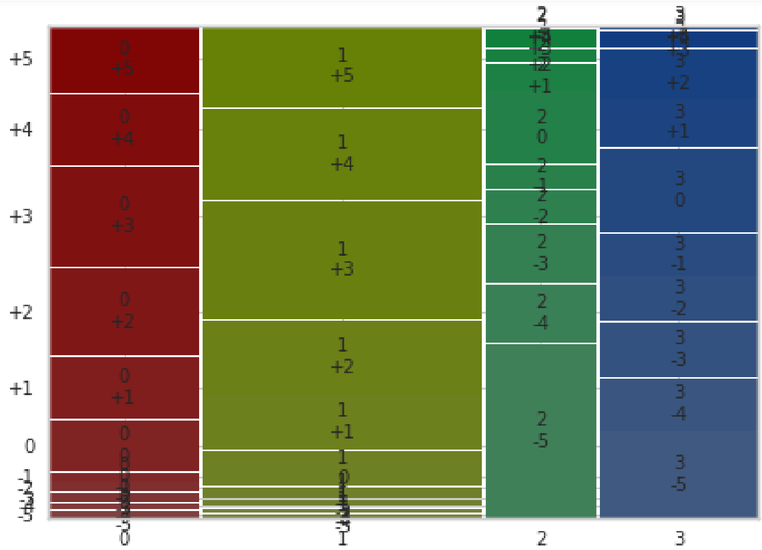
The fast food data set is not typical for data collected for market segmentation analysis because it contains very few descriptor variables. Descriptor variables – additional pieces of information about consumers – are critically important to gaining a good understanding of market segments. One descriptor variable available in the fast food data set is the extent to which consumers love or hate McDonald's. Using a simple mosaic plot, we can visualize the association between segment membership and loving or hating McDonald's. To do this, we first extract the segment membership for each consumer for the four-segment solution. Next we cross-tabulate segment membership and the love hate variable. Finally, we generate the mosaic plot with cells colors indicating the deviation of the observed frequencies in each cell from the expected frequency if variables are not associated (shade = TRUE). We do not require a title for our mosaic plot (main = ""), but we would like the x-axis to be labelled (xlab): R> k4 <- clusters(MD.k4) R> mosaicplot (table(k4, mcdonalds$Like), shade = TRUE, + main = "", xlab = "segment number") The mosaic plot in Fig. A.11 plots segment number along the x-axis, and loving or hating McDonald's along the y-axis. The mosaic plot reveals a strong and significant association between those two variables. Members of segment 1 (depicted in the first column) rarely express love for McDonald's, as indicated by the top left boxes being colored in red. In stark contrast, members of segment 4 are significantly more likely to love McDonald's (as indicated by the dark blue boxes in the top right of the mosaic plot). At the same time, these consumers are less likely to hate McDonald's (as indicated by the very small red boxes at the bottom right of the plot). Members of segment 2 appear to have the strongest negative feelings towards McDonald's; their likelihood of hating McDonald's is extremely high.

```
from statsmodels.graphics.mosaicplot import mosaic
from itertools import product

crosstab =pd.crosstab(df['cluster_num'],df['Like'])
#Reordering cols
crosstab = crosstab[['-5','-4','-3','-2','-1','0','+1','+2','+3','+4','+5']]
crosstab
```

Like	-5	-4	-3	-2	-1	0	+1	+2	+3	+4	+5
cluster_num											
0	5	3	6	6	6	33	41	58	66	47	44
1	4	4	2	6	13	43	65	90	143	111	99
2	84	28	28	16	11	35	13	6	9	0	0
3	59	36	37	31	28	58	33	33	11	2	0

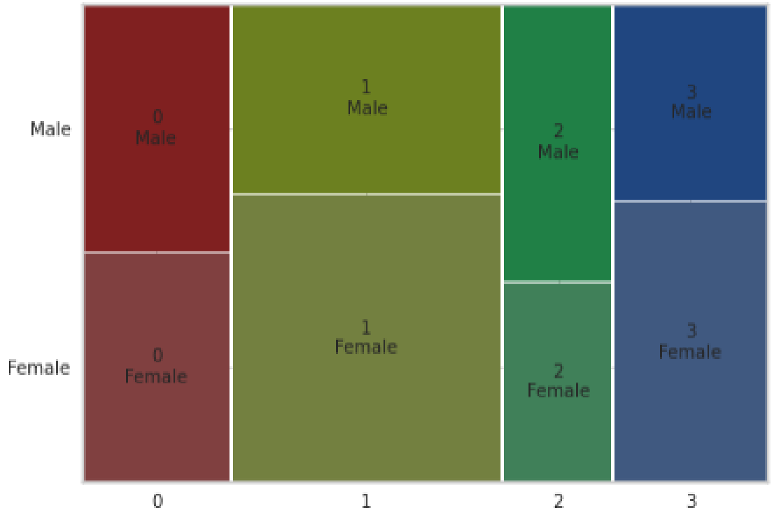
```
#MOSAIC PLOT
plt.rcParams['figure.figsize'] = (7,5)
mosaic(crosstab.stack())
plt.show()
```



```
#Mosaic plot gender vs segment
crosstab_gender =pd.crosstab(df['cluster_num'],df['Gender'])
crosstab_gender
```

Gender	Female	Male
cluster_num		
0	151	164
1	349	231
2	96	134
3	192	136

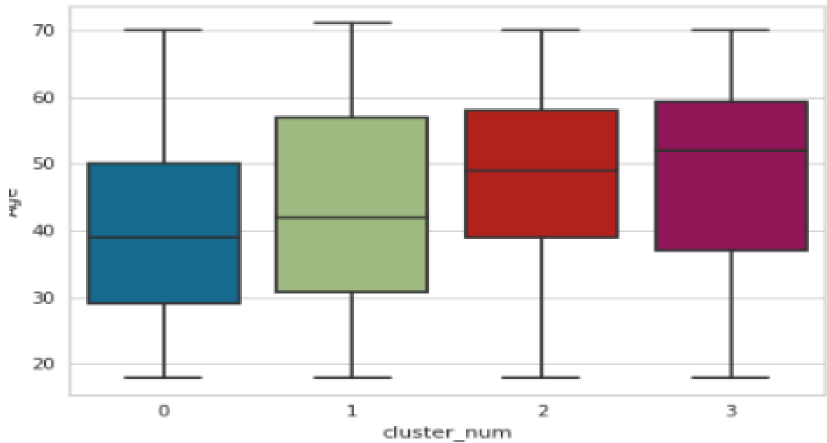
```
plt.rcParams['figure.figsize'] = (7,5)
mosaic(crosstab_gender.stack())
plt.show()
```




```
#box plot for age

sns.boxplot(x="cluster_num", y="Age", data=df)
```

```
<AxesSubplot:xlabel='cluster_num', ylabel='Age'>
```



For McDonald's, a profile of their target segments might include:

Blue boxes at the bottom of the second column), and nearly none of the consumers in this segment love McDonald's (tiny first and second box at the top of column two, then dark red third and fourth box). The fast food data contains a few other basic descriptor variables, such as gender and age. Figure A.12 shows gender distribution across segments. We generate this figure using the command: R> mosaicplot(table(k4, mcdonalds$Gender), shade = TRUE) Market segments are plotted along the x-axis. The descriptor variable (gender) is plotted along the y-axis. The mosaic plot offers the following additional insights about our market segments: segment 1 and segment 3 have a similar gender distribution as the overall sample. Segment 2 contains significantly more men (as depicted by the larger blue box for the category male, and the smaller red box for the category female in the second column of the plot). Members of segment 4 are significantly less likely to be men (smaller red box at the top of the fourth column). Because age is metric – rather than categorical – we use a parallel box-andwhisker plot to assess the association of age with segment membership. We generate Fig. A.13 using the R command boxplot(mcdonalds$Age ~ k4, varwidth = TRUE, notch = TRUE). Figure A.13 plots segments along the x-axis, and age along the y-axis. We see immediately that the notches do not overlap, suggesting significant differences in average age across segments. A more detailed inspection reveals that members ofsegment 3 – consumers who think McDonald's is yummy and tasty, but expensive – are younger than the members of all other segments. The parallel box-andwhisker plot shows this by (1) the box being in lower position; and (2) the notchin the middle of the box being lower and not overlapping with the notches of the other boxes. To further characterise market segments with respect to the descriptor variables, we try to predict segment membership using descriptor variables. We do this by fitting a conditional inference tree with segment 3 membership as dependent variable, and all available descriptor variables as independent variables: R> library("partykit") R> tree <- ctree(+ factor(k4 == 3) ~ Like.n + Age + + VisitFrequency + Gender, + data = mcdonalds) R> plot(tree) Figure A.14 shows the resulting classification tree. The independent variables used in the tree are LIKE.N, AGE and VISITFREQUENCY. GENDER is not used to split the respondents into groups. The tree indicates that respondents who like McDonald's, and are young (node 10), or do not like McDonald's, but visit it more often than once a month (node 8), have the highest probability to belong to segment 3. In contrast, respondents who give a score of −4 or worse for liking McDonald's, and visit McDonald's once a month at most (node 5), are almost certainly not members of segment 3. Optimally, additional descriptor variables would be available. Of particular interest would be information about product preferences, frequency of eating at a fast food restaurant, frequency of dining out in general, hobbies and frequently used information sources (such as TV, radio, newspapers, social media). The availability of such information allows the data analyst to develop a detailed description of each market segment. A detailed description, in turn, serves as the basis for tasks conducted in Step 9 where the perfect marketing mix for the selected target segment is designed.

Step 8 Selecting the Target Segments:

The Targeting Decision:

Market segmentation is a strategic marketing tool. The selection of one or more target segments is a long-term decision significantly affecting the future performance of an organization. This is when the flirting and dating is over; it's time to buy a ring, pop the question, and commit.

Answering the following two questions forms the basis of target segment decision:

1. Which of the market segments would the organization most like to target? Which segment would the organization like to commit to?

2. Which of the organizations offering the same product would each of the segments most like to buy from? How likely is it that our organization would be chosen? How likely is it that each segment would commit to us?

Market Segment Evaluation

Most books that discuss target market selection (e.g., McDonald and Dunbar 1995; Lilian and Rangaswamy 2003), recommend the use of a decision matrix to visualized relative segment attractiveness and relative organizational competitiveness for each market segment.

The aim of all these decision matrices along with their visualization's is to make it easier for the organization to evaluate alternative market segments, and select one or a small number for targeting. It is up to the market segmentation team to decide which variation of the decision matrix offers the most useful framework to assist with decision making.

Whichever variation is chosen, the two criteria plotted along the axes cover two dimensions: segment attractiveness, and relative organizational competitiveness specific to each of the segments.

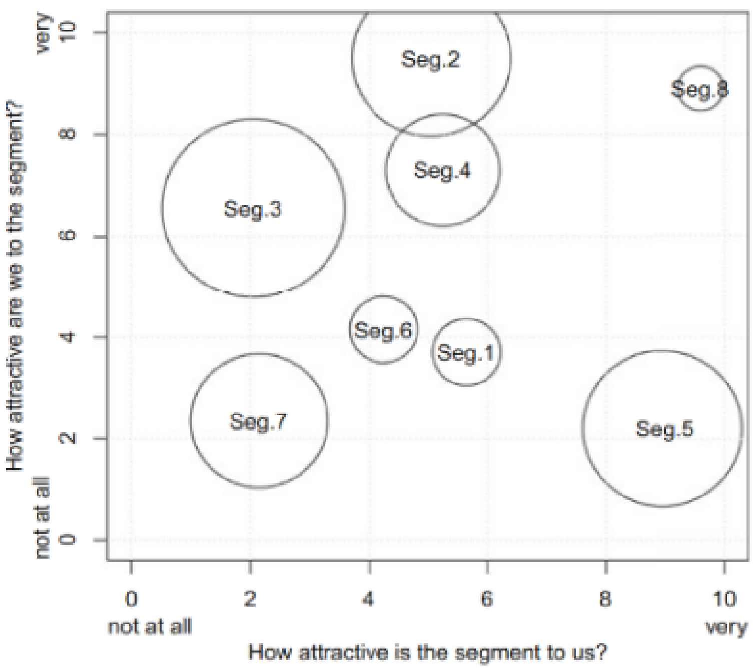
Using the analogy of finding a partner for life:

Segment attractiveness is like the question would you like to marry this person? Given all the other people in the world you could marry.

Relative organizational competitiveness is like the question Would this person marry you? Given all the other people in the world they could marry.

To keep segment evaluation as intuitive as possible, we label the two axes How attractive is the segment to us? And How attractive are we to the segment? We plot segment attractiveness along the x-axis, and relative organizational competitiveness along the y-axis. Segments appear as circles. The size of the circles reflects another criterion of choice that is relevant to segment selection, such as contribution to turnover or loyalty.

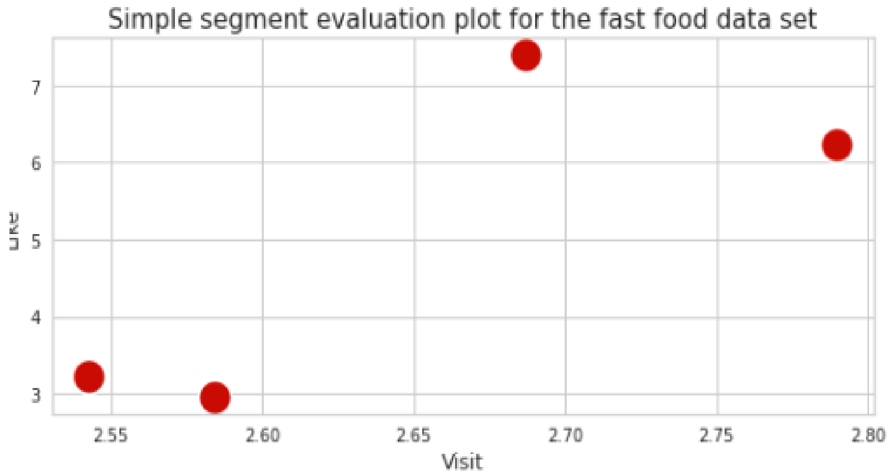
There is no single best measure of segment attractiveness or relative organizational competitiveness. It is therefore necessary for users to return to their specifications of what an ideal target segment looks like for them. The ideal target segment was specified in Step 2 of the market segmentation analysis. Step 2 resulted in a number of criteria of segment attractiveness, and weights quantifying how much impact each of these criteria has on the total value of segment attractiveness. To determine the attractiveness value to be used in the segment evaluation plot for each segment, the segmentation team needs to assign a value for each attractiveness criterion to each segment.



The segmentation team may eliminate from further consideration segments 3 and 7 because they are rather unattractive compared to the other available segments despite the fact that they have high profit potential (as indicated by the size of the bubbles). Segment 5 is obviously highly attractive and has high profit potential, but unfortunately the segment is not as fond of the organisation as the organisation is of the segment. It is unlikely, at this point in time, that the organisation will be able to cater successfully to segment 5. Segment 8 is excellent because it is highly attractive to the organisation, and views the organisation's offer as highly attractive. A match made in heaven, except for the fact that the profit potential is not very high. It may be necessary, therefore to consider including segment 2. Segment 2 loves the organisation, has decent profit potential, and is about equally attractive to the organisation as segments 1, 4 and 6 (all of which, unfortunately, are not very fond of the organisation's offer).

```
#Target segments

plt.figure(figsize = (9,4))
sns.scatterplot(x = "VisitFrequency", y = "Like",data=segment,s=400, color="r")
plt.title("Simple segment evaluation plot for the fast food data set",
          fontsize = 15)
plt.xlabel("Visit", fontsize = 12)
plt.ylabel("Like", fontsize = 12)
plt.show()
```



Step 9: Customising the Marketing Mix:

Implications for Marketing Mix Decisions

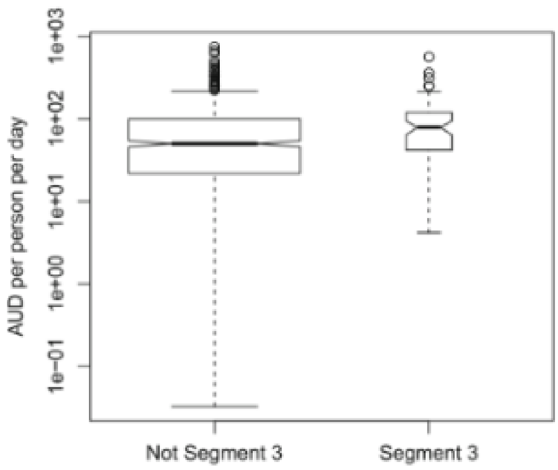
Marketing was originally seen as a toolbox to assist in selling products, with marketers mixing the ingredients of the toolbox to achieve the best possible sales results. In the early days of marketing, Borden (1964) postulated that marketers have at their disposal 12 ingredients: product planning, packaging, physical handling, distribution channels, pricing, personal selling, branding, display, advertising, promotions, servicing, fact finding and analysis. Many versions of this marketing mix have since been proposed, but most commonly the marketing mix is understood as consisting of the 4Ps: Product, Price, Promotion and Place.

Product

One of the key decisions an organisation needs to make when developing the product dimension of the marketing mix, is to specify the product in view of customer needs. Often this does not imply designing an entirely new product, but rather modifying an existing one. Other marketing mix decisions that fall under the product dimension are: naming the product, packaging it, offering or not offering warranties, and after sales support services.

Price

Typical decisions an organisation needs to make when developing the price dimension of the marketing mix include setting the price for a product, and deciding on discounts to be offered.

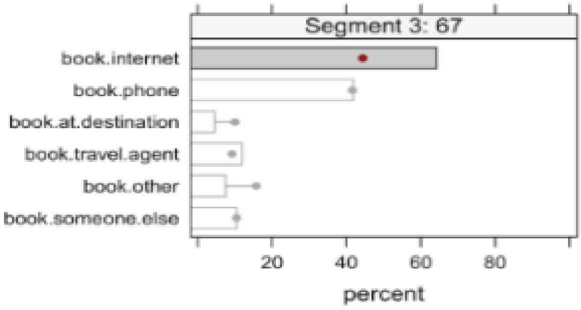


Place

The key decision relating to the place dimension of the marketing mix is how to distribute the product to the customers. This includes answering questions such as:

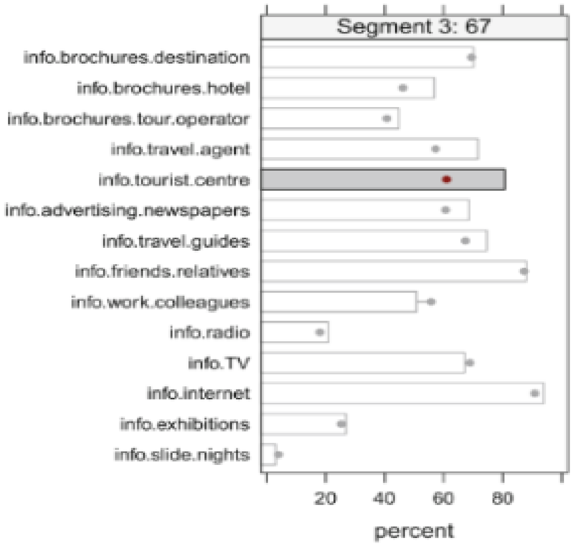
should the product be made available for purchase online or offline only or both;

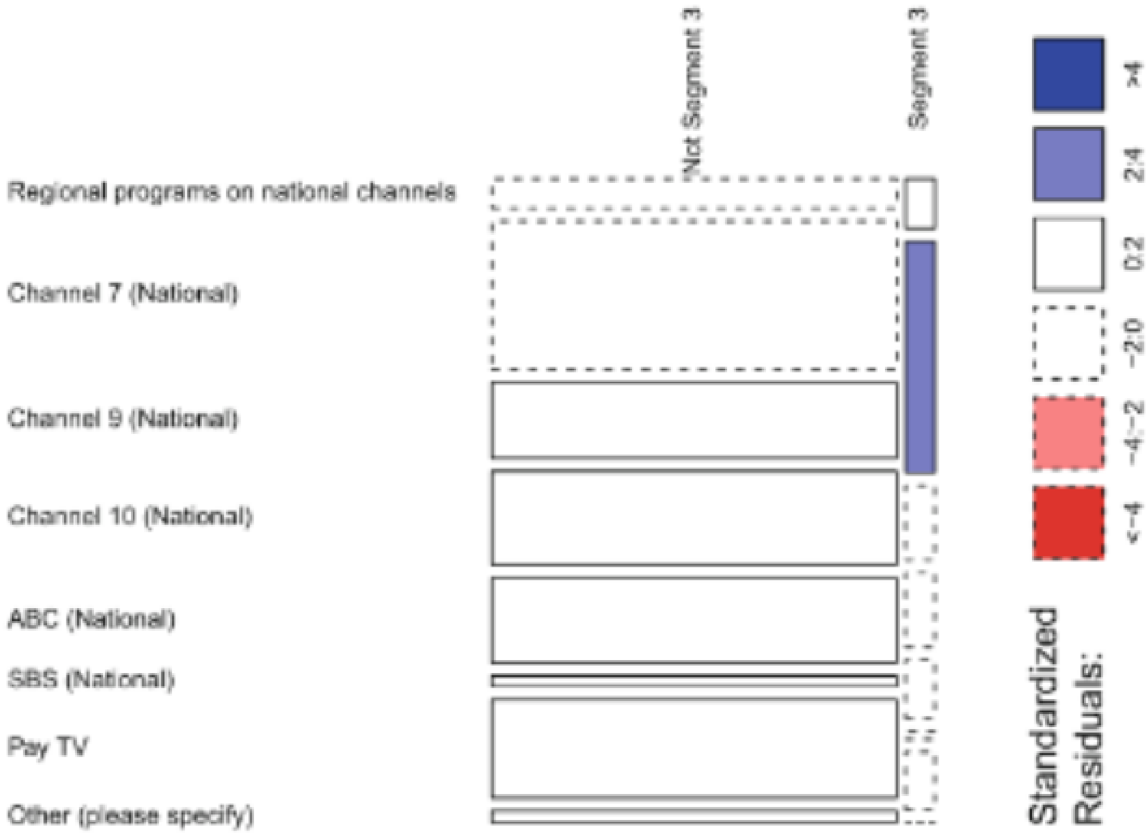
should the manufacturer sell directly to customers; or should a wholesaler or a retailer or both be used.



Promotion

Typical promotion decisions that need to be made when designing a marketing mix include: developing an advertising message that will resonate with the target market, and identifying the most effective way of communicating this message. Other tools in the promotion category of the marketing mix include public relations, personal selling, and sponsorship.





Not Segment 3
Segment 3
Regional programs on national channels
Channel 7 (National)
Channel 9 (National)
Channel 10 (National)
ABC (National)
SBS (National)
Pay TV
Other (please specify)
Standardized Residuals:
>4
2:4
0:2
−2:0
−4:−2
<−4

Contributed Git Hub Link's

Team Member Name's	GitHub Link's
Raksha	https://github.com/raksha2727/McDonalds-market-segmentation
Manjunath	https://github.com/ManjuKannavalli/Feynn_Labs-Market_segmentation_case_study
Nishanth	https://github.com/nishnai/R_to_Python_from_Market_Segmentation_Analysis
Budige Avinash	https://github.com/Avinashbudige/AI-ML