Summary Part

2) Specifying the ideal target Segment

in general, The target segment or the segments must be homogeneous, distinct, highly justifiable for the marketing mix, identifiable to everyone and reachable.

In this case study, the obvious choice they made to select the segment with positive perception of McD. but the management tried to understand the situation and tried to learn about the segments that are concerned among the customers.

3) Exploring the data

The dataset that has been used in the case study is the McD's customer feedback as per their orders. For the replicating the project I have used the same dataset from McD.

dataset link =>

The shape of the dataset is about (1453,15), That means there are 1453 records of data in about 15 attributes given by McD. Those features are named as 'yummy', 'convenient', 'spicy', 'fattening', 'greasy', 'fast', 'cheap', 'tasty', 'expensive', 'healthy', 'disgusting', 'Like', 'Age' , 'VisitFrequency', 'Gender'.

After cleaning and transforming the dataset and applying head() technique, we get 5 records of the dataset as an output. from output, the first respondent believes that McDonald's is not yummy, convenient, not spicy, fattening, not greasy, fast, cheap, not tasty, expensive, not healthy and not disgusting. This same respondent does not like McDonald's (rating of −3), is 61 years old, eats at McDonald's every three months and is female.

But as per output, the segmentation variables are verbal, not numeric(1's and 0's). so, for segmentation, we need numbers not words. TO get numbers from them, storing them into matrix and converting to Yes/No to numeric binary. For that extracting the first eleven columns from dataset because these columns contain the segmentation variables, and convert the data to a matrix. then Addition of 0 to logical matrix converts TRUE to 1 and FALSE to 0. Thus, Encoding is done.

After implying some of the basic operations like mean, variance, S.D, cumulative proportion, we are ready with the data for our model.

The last step is to plot the diagrams(like, clustering, PCA, etc.) for the given attributes which will be easy to understand for others.

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5) Extracting Segments

Extraction of segments is one of the main steps in this case. This step is divided into 3 sub-steps.

1) using K-means analysis.

2) using mixture of binary distributions.

3) using mixture of regressive models.

1) use of K-means:

We calculate solutions for the 2 to 8 segments using K-means with 10 random restarts. We extract between two and eight segments because we do not know in advance what the best number of market segments is if we calculate a range of solutions, we can compare them and choose the one which extracts segments containing similar consumers which are distinctly different from members of other segments.

The plotted Screenplot no distinct elbow : the sum of distances within market segments drops slowly as the number of market segments increases. We expect the values to decrease because more market segments automatically mean that the segments are smaller and, as a consequence, that segment members are more similar to one another Profiling Segment. Thus, this is not a good way to represent the segments.

A second approach to determining a good number of segments is to use stability-based data structure analysis. Stability-based data structure analysis also indicates whether market segments occur naturally in the data, or if they have to be artificially constructed. Global stability is the extent to which the same segmentation solution emerges if the analysis is repeated many times using bootstrap samples (randomly drawn subsets) of the data.

2) using mixture of binary distributions.

We calculate latent class analysis using a finite mixture of binary distributions. The mixture model maximises the likelihood to extract segments. In this, we are using the minimisation technique that opposed which we used in the K-means as Euclidean distance. The call to stepFlexmix() extracts two to eight segments (k = 2:8) using ten random restarts of the EM algorithm.

Then, We plot the information criteria with a customised label for the y-axis to choose a suitable number of segments. It plots the information criteria values AIC, BIC and ICL on the y-axis for the different number of components (segments) on the x-axis. As can be seen, the values of all information criteria decrease quite dramatically until four components (market segments) are reached.

If the information criteria are strictly applied based on statistical inference theory, the ICL recommends – by a small margin – the extraction of seven market segments. The BIC also points to seven market segments. The AIC values continue to decrease beyond seven market segments, indicating that at least eight components are required to suitably fit the data.

3) using mixture of regressive models

This substep mainly targets the market segment that love or hate for McD is driven similar perceptions. This segmentation approach would enable McDonald's to modify critical perceptions selectively for certain target segments in view of improving love and reducing hate.

We extract such market segments using finite mixtures of linear regression models, also called latent class regressions. Here, the variables are not all treated in the same way. Rather, one dependent variable needs to be specified which captures the information predicted using the independent variables. We choose as dependent variable by the degree to which consumers love or hate McDonald's. The dependent variable contains responses to the statement 'I LIKE MCDONALDS'.

First, we create a numerical dependent variable by converting the ordinal variable LIKE to a numeric one. We need a numeric variable to fit mixtures of linear regression models. The categorical variable has 11 levels, from 'I LOVE IT !' (+5) with numeric code 1 to 'I HATE IT !'(-5) with numeric code 11. Then we can either create a model formula for the regression model manually by typing the eleven variable names, and separating them by plus signs. Or we can automate this process in Python by first collapsing the eleven independent variables into a single string separated by plus signs, and then pasting the dependent variable(like into N). And, finally, we convert the resulting string to a formula.

6) Profiling Segments

The core of the segmentation analysis is complete market segments have been extracted. Now we need to understand what the four-segment k-means solution means. The first step in this direction is to create a segment profile plot. The segment profile plot makes it easy to see key characteristics of each market segment. It also highlights differences between segments. The second step is to ensure the plot is easy to interpret, similar attributes should be positioned close to one another. We achieve this by calculating a hierarchical cluster analysis. And the last step, s. Hierarchical cluster analysis used on attributes identifies – attribute by attribute – the most similar ones.

This becomes easy for McDonald's managers to interpret. They can see that there are four market segments. They can also see the size of each market segment. The smallest segment (segment 2) contains 18% of consumers, the largest (segment 1) 32%. The names of the segmentation variables (attributes) are written on the left side of the plot. The horizontal lines with the dot at the end indicate the percentage of respondents in the entire sample who associate each perception with McDonald's. The bars plot the percentage of respondents within each segment who associate each perception with McDonald's.

To understand the market segments, McDonald's managers need to do two things: (1) compare the bars for each segment with the horizontal lines to see what makes each segment distinct from all consumers in the market; and (2) compare bars across segments to identify differences between segments.