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Coursework: Marketing Toolkit
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Marketing Analytics Toolkit

This toolkit will consist of an overview of 4 analytical tools used in marketing: 1. Cluster Analysis, 2. Choice Models, 3. Conjoint Models & 4. Market Response Models.

Cluster Analysis

It is a form of exploratory data analysis where observations are divided into meaningful groups with common characteristics. It is used to classify a large group of heterogeneous customers (or firms and other objects) into a few homogenous parts known as clusters.

How can it help?

Cluster analysis may be a valuable data-mining technique for any company that wants to discover distinct groups of clients, sales transactions, or other sorts of behaviours and products. Insurance companies, for example, utilise cluster analysis to detect fraudulent claims, while banks use it for credit assessment.

How does it work?

Pre Processing: First, we must prepare our data for clustering, meaning there are no missing values and that features are scaled.

Select similarity measures: Next, based on the features, we choose the metric that best captures the similarity between the observations.

Clustering: Next, we use a clustering approach to divide our observations into clusters depending on how similar they are. Most importantly, we must examine the results of these clusters to see whether they offer any insightful information about your data.

Analyse: This requires a deep understanding of the problem and the information at hand.

The analysis you run on these clusters may need iterating on your clustering stages until you arrive at a meaningful grouping of your data. The first two phases will assist you in unpacking this process by providing a more in-depth view of what it means for two observations to be similar or, more particularly, different. We also must make sure that the features in our data set need to be comparable to one another.

Following the completion of the cluster analysis, a review of the segmentation findings should be performed to assess whether the produced clusters make intuitive sense. The following significant factors should be considered while evaluating the validity:

Identifiability: Do the resulting segments represent genuine customer segments, and can they be led using descriptors?

Stability: Will the derived segments change quickly over time?

Responsiveness: Will the targeted segments respond to the proposed marketing strategies?

Viability: Can the organisation accomplish its financial goals using the segmentation scheme?

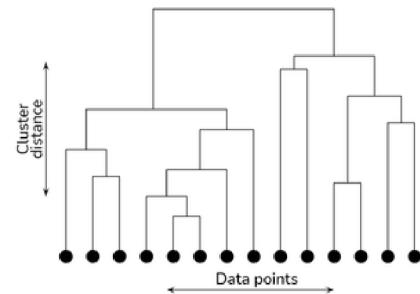
In the next two steps, we will employ the two most popular clustering methods: hierarchical clustering or k-means clustering.

These two clustering methods use euclidean distance as a measure of similarity between two customers. Euclidean distance is the geometric distance between two customers (or cases). Therefore, if we have a customer I and customer j, then we could express their Euclidean distance in terms of the following equation:

$$d(x, y) = \sqrt{\sum_{i=1}^n (y_i - x_i)^2}$$

Dendrogram

A dendrogram is primarily used to determine the optimal approach to assign objects (i.e., customers) to clusters.



The dendrogram's vertical axis reflects the distance or dissimilarity between groups. The horizontal axis depicts items (customers) and clusters. When the dissimilarity between the connecting clusters gets too great, the dendrogram is usually clipped.

Choice Models

A Choice Model is a mathematical/statistical model that predicts how a firm's marketing interventions, customer traits, and/or environmental circumstances impact the likelihood of an observed consumer choice or reaction.

As marketers, we want to know how features will relate to which product the customer will choose. We can use that information to predict what will happen to market share if we change our product choices. We use a **multinomial logistic regression** or the **multinomial logit model** to evaluate this.

How can it help?

They are used to predict a choice from a set of two or more options. The prediction is based on the features of each alternative. Logistic regression is a special case of multinomial logistic regression that we use with data on binary yes-or-no choices. Choice models have a lot of applications within marketing. We can use choice models to understand which features would make our products more desirable, and how to price a product based on how customers trade-off prices against other products.

How does it work?

The weightage (or coefficient) distribution: It tells what weightage each attribute would have needed for buyers to choose that product. Doing this lists the elements most likely to affect a customer's choice.

Predictive function: When we just observe a product's qualities, we may use the attributes and weights of the model to anticipate the decisions that a new group of consumers will likely make. This, in turn, can assist a business in segmenting and focusing on clients based on the likelihood of choosing them.

Market Share Simulation: By summing all client product selections, the model can be used to simulate the market share of a specific product category. It can also help managers plan their marketing campaigns.

Conjoint Analysis

Conjoint analysis is a survey research technique. The data for the conjoint analysis is generated by presenting the survey taker with a "choice problem". When survey respondents examine each response, they select the one they prefer, and a fresh set of options containing all of the information is shown. And so on, until each survey participant has chosen around 8 to 10 choices.

How can it help?

Conjoint Analysis is a powerful tool for enhancing product features. It is especially useful when limited resources allow for only a few product features to be included and the organisation must decide which features to prioritise. As a result, conjoint analysis is also referred to as trade-off analysis. Conjoint analysis may help you determine a product's price elasticity, which is important for choosing the ideal pricing point, understanding what customers are willing to pay for a new service or feature on a product, estimating demand for a new product, and assessing the value of a brand name.

How does it work?

In the Choice Task Model, a survey respondent is presented with many products side by side. While survey respondents believe they are seeing different products, the survey is just showing a random set of features displayed numerous times side by side. Because conjoint analysis is a probabilistic technique, the research will look for patterns in the decisions of hundreds of people after they have made thousands of combinations. It will look for patterns in which certain attributes make survey respondents more or less likely to buy a product when it is shown.

It will assign a score to each feature, indicating whether that feature increases or decreases the probability that the product will be chosen. This is referred to as the "part-worth utility score."

If we assume, that a product's overall appeal is the sum of its attractions, we can design any product from its desired sets of features and add up these part-worth utilities to acquire the product's overall utility score. We may employ a statistical formula to assess how much more or less likely that specific product is to be picked by customers than other things with which it may compete. This is known as the "preference share". We may estimate the preference share to predict potential demand for a new product release.

The conjoint formula is:

$$R(P) = \sum_{j=1}^{k_j} \sum_{i=1}^m \beta_{ij} x_{ij}$$

The utility ratings for each component may also be used to select the best product by simply selecting the characteristics from each form that maximise the chance of those products being selected in the market.

Market Response Models

Market response models are commonly used statistical tools for optimising advertising mixes and promotion methods. Response models rely on historical data to determine the best marketing mix. Experts use this information to change product prices and optimise marketing efforts.

How can it help?

Market Response Model look at how customers could react to marketing decisions while removing confounding variables that might be present when comparing a treatment to a control group. Marketing response models can determine if a certain BOR (brand/offering/relational) investment or marketing activity (e.g., marketing communications) has a direct causal relationship with customer or company outcomes. This helps in the selection of a range of brand investment methods and methodologies based on their financial impact.

How does it work?

There are two types of Market response models:

Top-down market model: The top-down market approach examines the market as a whole before breaking it down into bits and determining how much business one can gain in each of those particular components. These sections are known as segments, and a corporation can choose to target each segment individually. This is known as segmentation.

The bottom-up approach: Here, we select a basic unit that we can control as a business owner and establish the number of sales that the base unit may create. For example, if we sold a product to five customers and knew that at least one of them would convert into a very high-quality user, who used our product five times a month, two of them would take the gadget and utilise it once or twice a month and the other two may not use the device at all. In this manner, we will be able to anticipate our business by understanding exactly how our market and revenue will increase.

