EVALUATION OF DIFFERENT APPROACHES FOR MARKET SEGMENTATION AND A PROPOSAL

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I. INTRODUCTION :

One of the most popular subject in marketing area, today, is Market Segmentation. During the last few years, multivariate statistical techniques, such as nonmetric multidimensinol scaling, discriminant analysis, canonical correlation, and cluster analysis or numerical taxonomy, have been applied to a wide variety of business areas, especially behavioral sciences and marketing. Form consumer behavior theory we know that sets of variables, namely a set of buying behavior variables, a set of socioeconomic variables, and a set of personality characteristic variables should be taken into account in market segmentation. This complexity of market segmentation forces the marketing analyst to use multivariate statistical techniques for studying market segmentation. However it is relatively easy to apply these multidimensional statistical techniques by the available computer programs, such as BMDO series, to market segmentation problem, we have to keep at least two important points in our minds. The first point is that ali of these multivariate techniques are proximities or approximations. And the second point is that the available tests to test the results of the multivariate analysis are not so powerful and in some techniques there are no tests available at ali.

In this article we like to take a real life market segmentation problem, evaluate different approaches, and propose an original approach to solve the problem in terms of two criteria or points given above.

II. PROBLEM :

A marketing executive whose firm produces a line of medium - priced ($ 10 - $ 45) small appliances (can openers, toasters, coffee makers, blenders, etc.) has just attended a meeting at which a number of techniques for studying market segmentation have been presented. He briefly recalls what he understood four different analysts to say at that meeting.

Analyst A suggested a multi-dimensional scaling and unfolding analysis. Data on consumer's (1) judgements about similarities of different brands, (2) preferences across brands and (3) perceptions of the attributes of individual brands and of each consumer's ideal point in a multi-dimensional space.

Analyst B urged a discriminant analysis to determine the household characteristics (e.g., income, family size, life cycle stage, occupation, value of dwelling, amount of entertaining, etc.) which tend to differentiate those who have purchased a particular brand from those who have not. Analyst B also mentioned, as an apparent afterhought, that the analysis might be performed to determine the characteristics which tend to differentate those who are heavy buyers (e.g., own many small appliances) from those who are not.

Analyst C was a proponent of hierarchical clustering. He wanted to consider each consumer as a point in multi-dimensional space. The consumer's location would depend upon the value of a number of variables for that consumer. Analyst C did not seem too concerned about what variables were employed, but he used a number of dimensions of behavior in buying a given product (e.g., quantity purehased, price paid, amount of shopping, number of information sources consulted) in his example. He aggregated consumers into clusters based upon their similarity; distance separating two consumers in this multi-dimensional space being used as an inverse measure of similarity.

Analyst D claimed that each of his colleagues had really missed the point. He said that none of the techniques proposed by A, B, and C corresponded to the procedures one would employ, if one only knew individual consumer's response funetions. Analyst D then presented a rahter lengthy mathematical development in which he demostrated his ability to find the maxima of functions of several variables.. A numerical example demostrated that, if one knew individual consumer's response funetions and the firm's cost function, then one could in fact identify the most profitable market segment structure.

Marketing executive thought such techniques might be helpful in making three kinds of decisions, namely: (1) the kinds of retail outlets on which to concentrate his efforts to obtain distribution; (2) the kind of media to buy for dissemination of his advertising message; (3) the kind of design (e.g., price level, specific features, general attractiveness) to aim in developing up-dated versions of the present products.

III — BRIEF DISCUSSION OF DIFFERENT APPROACHES FOR MARKET SEGMENTATION :

Here, we like to concentrate on some explanation of four different approaches and, especially, discussion of these approaches in terms of our specific problem given in the previous section of this article.

Under the light of the decision problems of the marketing executive, our discussion would be focused upon the market segmentation problem where different marketing strategies are directed toward different target groups of consumers.

First of ali, market segmentation approaches provide a means of aggregating consumers into market segments. The important points in market segmentation are; (1) market segmentation is an aggregation problem, (2) the choice of the level of agregation on the number of market segments, and (3) measures should be used in deciding which consumers to aggregate.

We like to begin our discussion with the third point mentioned above. Theoreticaliy, the best measure in deciding which consumers to aggregate is based on similarity in consumers' reponse functions (or characteristics) to the different market stimuli. This approach was proposed by the Analyst D. Assuming that we can obtain each consumer's response functions to each market stimuli, such as price, advertising, salesmen, etc., and the cost of segmentation, then it is easy to get the optimum market segmentation strategy. The procedure to get the optimum market segmentation strategy is as follows (for price stimulus);

Maximize $\Pi = TR - TC$ .... (I)

where Π = total profit,

TR = total revenue,

TC = total cost (including the market segmentation cost)

Since TR $= \sum_{i=1}^{n} P_i Q_i$

where n = number of consumers,

P_i = consumer i's demand (or response) function

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Q_i = the quantity of product on brand which is purchased by the $i \frac{th}{\quad}$ consumer

Given that we know each consumers'a response (or demand) function, in this case response in terms of price, then we can easily get the TR by multiplying each consumer's response function, P_i, by the quantity purchased, Q_i, and summing them across ali the consumers.

Since TC is given then to maximize the total profit, we have to get first partial derivatives for each Q_i, of the equation (I) and equate each partial derivatives to zero. Then we have to solve each equation for the values of Q_i s and P_i s. To check whether or not those Q_i s and corresponding P_i s correspond to the maximum, we can take the second partial derivatives for each Q_i and the results must be less than zero.

The process explained above is complete disaggregation.

The optimum level of aggregation could be found by moving from complete disaggregation to complete aggregation. The criterion in deciding which consumers to aggregate is to aggregate first two consumers who have the most similar response funetions. To do that we must evaluate the profit associated with the optimal strategy for each possible mergins of a pair, n(n-1)/2 of the n consumers. Then we have to continue the aggregation process in the same manner. Then we should find the most profitable market segmentation strategy, or number of market segments. (Note that segmentation cost can be included to the analysis at the last aspect and in this case, which is better, total net profit, Π^*, could be found as such; $\Pi^* = \Pi -$ cost of segmentation. And the segmentation strategy which provides the maximum net total profit, max. Π^*, must he chosen as an optimal market segmentation strategy).

Of course, the same process can be applied to the other market stimuli, such as advertising, ete.

Unfortunately this approach does not have any practical value, since individual response funetions are generally unknown and almost impossible to predict. For this reason, we would drop the Analyst D's approach from our discussion.

Now, the market segmentation problem would he based on the measures of similarity which are surrogates for response function similarity. Different approaches, nonmetric multidimensional scaling, diseriminant analysis, and cluster analysis, can be used in this respect.

Nonmetric multidimensional scaling proposed by the Analyst A is, essentially, an approach to find geometric model of perceptions about stimuli, products, services, advertising, etc., from similarities data, locate the ideal points of individuals from preference ranks of stimuli, and fit property vectors to the configuration from attribute data.

Nonmetric multidimensional scaling by itself can be used for market segmentation purposes by clustering (or grouping) the ideal points which are elose to each other (or their interpoint distances are shorter) and describing these groups (or clusters) on the best fitted property vectors (or attribute vectors). But since the best fitted attributes would be only at most two or three and the degree to which the groups' possession of these attributes are measured at ordinal level, such as high usage rate, etc., this technique is a restricted and not precise technique for market segmentation. However, it can be used for solving especially the third problem (since it involves the customers' perceptions of product versions) and for solving the second decision problem (for media selection).

However, we do not propose to use this method by itself for solving these three decision problems.

The diseriminant analysis proposed by the Analyst B is the analysis to determine the variables which tend to differentiate a priori seleeted (or decided) two or more groups from each other. In our problem, since it is not possible to identify (a priori) the customer groups, we do not propose this method by itself for the market segmentation purpose.

The hierarchical cluster analysis proposed by the Analyst C is an analysis to find the natural groupings based on similarities of objects or individuals on overall variables. No priori grouping is necessary (contrast to the diseriminant analysis) and relationships need not be linear (contrast to the discriminant analysis). The resulting clusters are deseribed by the average values of the clusters on each variable, those are called centroid values. However, there are some weaknesses of the cluster analysis, such as there is no statistical test available for cluster analysis and it is sometimes confusing to find out where to stop or optimum number of clusters. To overcome the second weakness, we have to eheck the every step of clustering from practical (or pragmatic) point of view to determine whether or not resulting clusters make sense in terms of our knowledge about the phenomenon, existing theory, and past research results.

IV. CONCLUSION AND PROPOSAL:

We do propose cluster analysis as the main approach for the three decision problems mentioned. To answer those decision problems, we propose to first cluster the customers based on buying behavior variables and then, within each cluster, cluster the customers, who are similar in buying behavior, based on socioeconomic, demographic and personality variables. In the final clusters, we expect to find the individuals (or customers) who are similar in decision processes. However, the first stage clustering results seem more important for answering to decision problem 1 and 2, the second stage clustering results (clusters) can be very useful for answering to problem 2 and 3. We also propose to use nonmetric multidimensional analysis in order to reduce the dimensions in the cluster analysis.

After useful and meanigful clusters and their centroid values are determined, we also propose to use thc discriminant analysis by using the resulting clusters from cluster analysis as a priori groups and the variables found to describe the centroid values of clusters as independent (or predictor) variables. Then, we can use this discriminant analysis to find out whether or not those groups (or clusters) can be discriminated by these variables and the variables' relative importance to differentiate the groups found in the cluster analysis. The variables with high relative importance measure could guide us in choosing the kind of media to buy for dissemination of the advertising message and the kind of design to aim for developing up-dated versions of the present products. Of course, the question 1, the kinds of retail outlets on which to concentrate the firm's efforts to obtain distribution, could be answered from this analysis.

In summary, since there is no test available to test the results of the cluster analysis, we propose to use the discriminant analysis as a mean of statistical test to test the results of the cluster analysis. In addition to this, we also propose to use the multidimensional scaling to reduce the variable dimensions.

BİBLİOGRAPHY

For readers who want to explore their knowledge about the multivariate statistical techniques, a list of the relevant publications is given below.

P.E. Green and D.S. Tull «Research for Marketing Decisions» Prentice - Hail, N.J., 1970, Ch. 7, 11, and 13.

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