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ABSTRACT

Because cable channels lack the resources of the major broadcast networks, they must resort to "narrowcasting" to obtain a market niche. Finding that market niche is thus a key to any cable channel's survival. This chapter describes an approach to planning the programming of a cable channel, which enables it to carve out a unique market niche which has the highest possible audience or highest possible revenue. The positioning of a new cable channel and the repositioning of an existing cable channel are discussed.

INTRODUCTION

For many years the television environment in the United States was ruled by the three major networks: ABC, CBS, and NBC. In some large cities independent stations enjoyed a sizable share of the audience, but generally speaking the networks' combined share of audience was very large. As recently as 1977 the estimated network share of the prime time audience was 91%.

Cable television began as a way of providing programming to isolated, rural communities. In the last ten years, however, cable penetration has exploded from only 19% of US households in 1979 to over 41% of US households in 1985 (Television Digest 1985). Projections of 1990 cable penetration range from 54% (DMB&B 1986) to 58% (Kaatz 1985), and a conservative projection estimates a 64% penetration by 2000 (Krugman and Rust 1987).

A result of the increase in cable penetration has been a decrease in the audience share enjoyed by the three networks. From 91% in 1977 it has steadily fallen to 72% in 1985, and is projected to decline to 61% in 1990 and 54% in 2000 (Krugman and Rust 1987).

It is clear that cable is becoming an increasingly important player in the television game. Cable's increasing audience will bring in higher advertising revenue, all other things being equal. In fact, the increase in cable revenue should outstrip its increase in audience, due to an increasing trend in the revenue generated per cable household, even after adjusting for inflation (Krugman and Rust 1987).

These financial trends indicate that the cable environment is likely to be very dynamic in the coming years, with many new channels formed, many old channels dying, and many existing channels renovated to cope with competitive pressures. An important question is: how should a cable channel plan its programming in order to compete successfully?

Marketers talk about this issue as being "product positioning". What is referred to is the position of a product in perceptual space. In other words two products which are very similar will be close to each other in perceptual space, while two very different products will be far apart.

All other things being equal, it is advantageous to be positioned uniquely, with no close competitors, since that means the product will monopolize that part of the market. Cable theorists have realized this for a long time. They have spoken of cable programming as "narrowcasting", aiming for a small audience segment, rather than "broadcasting" to the masses. From a financial standpoint this makes a great deal of sense. The cable channels lack the financial resources to compete head-to-head with the major networks for the mass audience. Therefore they instead seek smaller, more specialized audiences whose needs they can meet more completely.

The problem for the cable channel then is how to locate an appropriate market niche. What programming needs are not currently being satisfied by the existing cable lineup? To answer this question we must first map the audience's perceptual space, find out where the existing channels are perceived to be, and then position the cable channel where it will have the most viewers and the least competition.

THE STRATEGIC APPROACH

Imagine three television viewers: Doug, Judy, and Mark. Doug is a sports fan. He watches major sports events on the major networks, and also enjoys watching ESPN regularly. Judy, on the other hand, prefers the fine arts, and spends most of her viewing hours watching PBS and the Arts

Network. Mark is a movie buff. He watches network movie presentations, and often tunes to HBO and Cinemax.

Let us assume that most people perceive programs in the same way (although they may not <u>prefer</u> the same programs). In perceptual space, then, most sports programs would be grouped close together, movie programs would be grouped together, and arts programs would tend to be grouped together. It is useful to imagine viewers mapped in the same space. For example Doug would be mapped close to the sports programs he watches, Judy close to the arts programs, and Mark close to the movies.

If a cable channel is to have a unique identity, in order to narrowcast successfully, it needs also to occupy a specific position in perceptual space. For example, ESPN is undoutedly intending to be perceived as similar to network sports broadcasts. It would then be positioned in perceptual space close to the network sports programs, and would probably be attractive to viewers like Doug.

In other words we may imagine a space which contains viewers, network programs, and cable channels, with viewers tending to watch network programs and cable channels which are close to their "ideal points". A new or repositioned cable channel would then seek to position itself in perceptual space close to as many viewer ideal points as possible, yet as far from competing cable channels as possible.

The density of the viewer ideal points may be visualized as a surface with mountains and valleys. Mountains would be places in the perceptual space where there are many viewers, and valleys would be where there are few viewers. It would be best for a cable channel to position itself in a "mountainous area" unless there is too much competition there.

Finding the best positioning involves trading off potential audience against existing competitive strength. The next section outlines a mathematical method for doing this, and obtaining an optimal market position.

But how does the optimal market position translate to programming? The prescribed market position may be characterized by the programs and networks which are close to it. For example if ESPN and network sports programs were near the optimal market position, the inescapable conclusion would be that a new sports channel was in order. On the other hand if the new position was between network movies and fine arts programs, then the indication might be to have an art and foreign film network.

Repositioning is also interpretable in this way. For example suppose ESPN's suggested optimal repositioning would move it in the direction of network golf broadcasts. That would be a signal to show more golf.

The next section discusses some of the techniques which may be used to implement this strategic approach.

METHODOLOGY

In order to capture consumers' perception of competing cable channels we propose to use multidimensional scaling. Multidimensional scaling refers to a set of procedures designed to spatially represent proximities between a number of stimuli. It transforms unidimensional expressions of relationships into multidimensional expressions of the same relationships.

Any phenomenon (product, service, image, aroma, etc.) can be thought of having both perceived dimensions and objective dimensions. Multidimensional scaling techniques enable researchers/managers to represent these dimensions spatially; to create visual displays that represent the dimensions perceived by the respondents while evaluating stimuli (brands, objects, etc.). This visual depiction helps the researcher better understand similarities and dissimilarities between objective and perceptual dimensions.

When individual perceptions of stimuli are obtained from respondents, a wide variety of techniques or procedures may be used, but the resultant data may be generally categorized as preference data, similarity data (proximity data), or ideal points. These data serve as the basis for using multidimensional scaling techniques to derive the perceptual dimensions used by the respondents to judge the similarity of, and preference for ideal stimuli.

An ideal point represents the most preferred combination of perceived attributes (on all relevant attribute dimensions). The position of the ideal point on this perceptual map would also be related to relative preference of all other stimuli. The ideal point position is determined by the assumption that the rank order of preference for a subject should correspond to the rank order of the distances of the stimuli from the position of the subject's ideal point.

Ideal point models, which jointly map the products under consideration and the consumer ideal points, are widely used in marketing to develop product positioning and segmentation strategies. These joint maps help identify gaps or opportunities in the market and also determine whether these positions will generate adequate demand. Hence this technique helps capture individual differences in preference, which is of prime importance to cable programmers.

Some of the scaling algorithms developed in the recent years include ALSCAL (Takane, Young, and Leeuw, 1977), MULTISCAL (Ramsey, 1977), the

Probabilistic approach (Zinnes and MacKay, 1983), and the Pick-Any algorithm (Levine, 1979).

Proposals for heuristic solutions of the postioning problem based on the joint map of products and ideal points have been made by Kuehn and Day (1962), Pessemier (1975), Shocker and Srinivasan (1974), Urban (1975), Brockhoff and Albers (1977), and Zufryden (1979) to name a few. These approaches, which give an analytical formulation of the problem, differ mainly in the underlying behavioral hypotheses.

Shocker and Srinivasan (1974) assume that the distance between the ideal points and the perceived location of the product is associated with a purchase probability less than one and greater than zero. On the other hand Brockhoff and Albers (1977) and Zufryden (1979) base their model on the assumption that a consumer chooses the product which is closest to his/her ideal point with a probability of one. DeSarbo and Hoffman (1986) propose a threshold unfolding model where a product is chosen whenever it is closer than a critical (threshold) distance.

Gavish, Horsky, and Srikant (1983) consider a joint space of ideal points and products, and plot consumer indifference curves, which are elliptical in shape. The shape of the ellipses are determined by the importance a consumer places on the attributes. They show that the optimal location for positioning a product is at the intersection of the maximum number of ellipses. Hence if the product is placed within the indifference ellipse for a consumer, it is assumed that he/she will choose it.

From the point of view of a continuous density function of ideal points, the models described above all estimate market share for product locations as though they assume that there is positive density only at the sample ideal points. It is intuitively reasonable to expect a positive density of ideal points all over the space, and especially in the areas near the existing sample ideal points. The density model used in this paper has been used to position radio stations (Donthu, Rust, and Lynch 1987) and to evaluate market areas (Donthu and Rust, 1987).

From the density function point of view, most current positioning models assume density "spikes", representing positive density only at the ideal points, with a zero density elsewhere. By contrast, the nonparametric density approach smooths these spikes by assigning some probability of having ideal points to the region around the sample ideal points. Figure 1 illustrates the density estimation depiction of the direct ideal point approach, and Figure 2 shows the corresponding density of the ideal points estimated by nonparametric density estimation (to be discussed elsewhere in this section).

It is usually very difficult to make a priori assumptions about the distribution of these ideal points. In the past Benson (1965) used hypothetical distributions of consumer ideal points, while Kamakura and Srivastava (1986) assumed that the ideal points within a segment were normally distributed. In this paper we use a very flexible method of density estimation known as kernel density estimation. This method of density estimation can flexibly capture various shapes based on the distribution of the ideal points in the joint map of products and ideal points.

3.1 The Proposed Method

The proposed model uses a joint map of consumer ideal points and perceived locations of competing cable channels as an input. We assume that this is given by a multidimensional unfolding algorithm using viewing preference data. The model then estimates the density function of the ideal points and uses that to estimate audience shares for various possible channel positionings. The model may be used to estimate the optimal location for a new or repositioned product.

We will first discuss the kernel density estimation technique and then discuss the mathematics of the proposed density model for flexible ideal point density estimation and product positioning.

Kernel Density Estimation

Most of the literature on density estimation is of a highly technical nature with little consideration for possible application. Useful sources which give the flavor of the subject from various points of view are Boneva, Kendall and Stefanov (1971), Wegman (1972), Rosenblatt (1971), Fryer (1977), and Silverman (1986).

The contemporary study of fully non-parametric density estimates began with Rosenblatt (1956), who first explicitly introduced the kernel estimate. The kernel density, f(x), is defined in d dimensions as:

$$f(\underline{x}) = (nh^d)^{-1} \sum_{i=1}^{n} K(\underline{x}-\underline{x}_i)/h)$$

where K is the kernel function, h is the smoothing factor or window width, n is the number of data points, and $\underline{x}_i$ are the data points.

If the kernel function is defined for all values of $\underline{x}$, then $f(\underline{x})$ has a positive density over the entire space. The density is the sum of n kernel functions, each centered at the observed points. Regions of the space in which there are many data points have a high density, while regions in which there are few points have a low density. The actual estimation, however, is continuous and not by regions.

The choice of the kernel function and smoothing factor are to some extent arbitrary. The choice of an optimal kernel function was considered by Epanechnikov (1969) and Silverman (1978). They showed that the choice of the kernel function is not very crucial and most functions, including normal, and uniform, give near optimal results, even with small sample sizes.

The smoothing parameter h dictates to what extent the density surface will follow the data. A large h results in a smooth-looking surface, while a small h results in a surface which is more lumpy. The problem of objectively choosing the value of h is a subject of current research, and several objective and partially objective methods have been suggested; see for example, Woodroofe (1970), Parzen (1979), and Silverman (1978 and 1980).

Density estimation techniques have been used for many years in statistics and mathematics for exploratory analysis, confirmatory analysis, and data presentation. Application in marketing and marketing research have included market area analysis (Rust and Brown, 1987; Donthu and Rust, 1987), nonparametric regression (Rust, 1986), and conjoint analysis (Brown and Donthu, 1987). The technique suggests itself naturally for flexibly estimating the density of ideal points to develop an aggregate model of choice.

Audience Share Estimation

Given the estimated density function of the ideal points, along with assumptions about how distance is related to choice, we may then estimate market share for any product location in the joint space.

The probability P_{ij}', that person i selects channel j' is assumed to be the ratio of utility of channel j' to the total utility of all J channels under consideration (Luce, 1959; Schonemann and Wang, 1972):

$$P_{ij} = \frac{U_{ij'}}{\sum_{j=1}^{J} U_{ij}} \qquad (1)$$

This formulation has been previously used in several models (e.g., Schonemann and Wang, 1972; Shocker and Srinivasan, 1974).

The joint Euclidean distance between subject i and cable channel j obtained from the unfolding map (Coombs, 1964) is:

$$d_{ij} = \sum_{k=1}^{K} (x_{ik} - y_{jk})^2 \qquad (2)$$

Hence the distance between the ideal points and the channels can be determined using (2), where X_{ik} and y_{jk} are locations of subject i' and channel j respectively. Finally, we postulate that these distances d_{ij} relate to utility U_{ij} as:

$$U_{ij} = \exp(-c\, d_{ij}^2) \qquad (3)$$

where c is a constant between 0 and 1. This formulation has been used by Schonemann and Wang (1972). A different relationship might just as easily be used and should not invalidate the proposed method.

Now for cable channel j' under consideration, the audience share is estimated by integrating the product of the density and the probability across the entire surface:

$$\text{Audience Share } ASj' = \int_{\underline{R}^k} g(\underline{x})\, P_{ij'}\, d\underline{x} \tag{4}$$

where $g(\underline{x})$ is not known, but may be estimated using nonparametric density estimation.

Substituting P_{ij} (from (2)) in (4) yields:

$$Asj' = \int_{\underline{R}^k} g(\underline{x}) \frac{\exp\,[-c((x_{i1} - mj) + (x_{12} - nj')^2]}{\sum_j \exp\,[-c((x_{i1} - mj) + (x_{i2} - nj)^2)]}\, d\underline{x} \tag{5}$$

The expression for market share in (5) may be estimated using a fine grid (as it does not have a closed form solution). Hence given the density function $g(\underline{x})$ of the ideal points, and the perceived locations (mj, nj) of the existing channels in the same map, it is possible to estimate the audience share for a new cable channel location (mj', nj') in the same place.

Differentiating the expression (5) with respect to mj and nj respectively and setting them equal to zero we can approximate the optimal location for a new or repositioned cable station. The resulting location will maximize the market share for this new station. This process involves Taylor series approximation of the market share and Newton-Raphson method of numerical optimization, as explained in Donthu (1986).

AN ILLUSTRATIVE EXAMPLE

To demonstrate the potential usefulness of the methodology described in the previous data, we obtained data from a sample of 150 households from a medium-sized Southwestern city. The example is for illustrative purposes only, and no claims are made regarding its generalizability to the national cable audience. National application would require several refinements, such as obtaining a national sample and making provisions for the unavailability of particular cable channels in some markets. Nevertheless the analysis presented here should be suggestive of what a larger-scale analysis might accomplish.

We collected viewing preference data from a systematic random sample of respondents in a large Southwestern city. The data were collected using telephone interviews. Respondents were included in the study only if they received cable service.

The respondents were first asked to list four of their favorite network and public television programs. Second, they were provided with a list of fourteen cable television channels and were asked to evaluate each of these on a scale of one to five. A score of five represented that they were very likely to view that cable channel and a score of one represented that they were not very likely to view that cable channel. They were also required to identify channels with which they were not familiar or did not receive. Demographic data such as sex, age, student/non-student, and home zip code were also collected for classification purpose.

The ratings data regarding the cable stations were used as an input to the ALSCAL (Takane, Young, and Leeuw, 1977) unfolding algorithm, which provided the joint map of respondent ideal points and the fourteen cable channnels used in this study. The joint map is presented in Figure 3. The numbers (one through fourteen) represent the cable channels listed in Table 1. Other details on this table will be discussed later in this section.

From the density function perspective, the ideal point model would represent each of these sample ideal points as a spike to estimate the market share for the various locations in space. However, the density model proposed in this paper uses the estimated density function of these ideal points. The kernel density function of the ideal points is shown in Figure 4. Figure 5 is the corresponding contour map of the kernel density map. This gives us an alternative picture of the density of the ideal points.

The density model was used to estimate the market shares for all cable channels used in this study. Table 1 shows the audience share predictions using the density approach. It is important to note that these estimates are based on the small sample used in the study and assumes that the market consists of these fourteen cable stations only. Hence the estimated figures may not match the published shares.

Now assuming that a new cable channel has decided to enter the market, we deal with the issue of positioning this new channel to maximize the share of the cable audience. We will also identify network programs that are associated with this new channel location, in order to make the positioning strategy meaningful.

The estimated optimal location for the new channel fifteen is shown in Figure 3. The predicted change in the market's market share structure after station fifteen enters the market is shown in Table 1. This position is predicted to draw customers away from existing cable channels and provide the new channel with maximum audience share.

It would also be possible to maximize other criteria, such as advertising revenue, instead of audience share. That would involve weighting the respondents appropriately. For example if high ratings in the women 18-49 age group were advantageous in increasing ad revenues, then respondents in that segment could be weighted greater. The remainder of the approach would remain exactly the same.

It is not always necessary that a cable channel reposition itself to maximize its market share. For any location (including sub-optimal ones) the model may be used to predict the audience share. Figures 6 and 7 are the plots of expected market share for the new cable channel at different locations in the space. From the figures it is clear that the optimum location determined by the proposed algorithm is indeed the global optima.

It is also important that the manager of the cable channel understands what the optimal location means. In this application, network and public television programs are used to describe locations in the space. Hence unlike other MDS applications it is not very important to name directions (or dimensions) in the space. Here it is more important to associate cable channel locations in space with images of television programs.

The favorite television programs listed by the respondents were placed at the centroids of the respondents who listed them. For each cable channel the list of programs associated with its prescribed location in the perceptual space was determined using the plot of the distance of the program from the channel versus the conditional probability that a channel will be chosen given that the program is chosen. The conditional probability is the ratio of the number who listed the program and were very likely to watch the cable channel to the total number of people who listed the program. An exponentially decreasing curve was fitted to the data (see Figure 8).

Figure 8 is an illustration of the probability versus distance plot discussed above. Here on the horizontal axis we have distances of the program from the channel in the map, and on the vertical axis we have the probability associated with each program. All programs to the left of the dotted line are closely associated with the location of the cable channel under consideration, and hence they are associated with the channel.

Given the fitted exponential curve, a program was inferred to be associated with a channel if the inferred conditional probability exceeded 0.5. Geometrically this means that we may construct a circle around each channel location, with programs found within the circle inferred as associated with the channel. This provides a surrogate for channel identity. As a result, each cable channel's image may be characterized by its set of associated network or public television programs.

In the case of the new cable channel the following television programs were strongly associated with its location on the perceptual map:
1) 60 Minutes, 2) Nightline, 3) Magnum PI, 4) Mike Hammer, 5) Murder She Wrote. Hence this location was perceived to be associated with investigative news reporting programs or action/mystery shows.

This could be used to design the programming content of the new cable station. The programming implication would be that either a news channel or an action/mystery entertainment channel should be contemplated.

SUMMARY AND CONCLUSIONS

This chapter describes how a new or existing cable channel may identify a programming hole, and use that information to position (or reposition) the channel's programming. The general idea is to supply programming for viewers whose needs are not currently being met. It is assumed that a cable channel, unlike the major broadcast networks, should seek to occupy a very narrow, specific market niche.

It is shown how survey data may be used to produce a map which simultaneously maps viewers, network programs, and cable channels. From this map, the distribution of viewing preferences in the population is estimated. Based on the estimated preference distribution, a cable channel may consider the projected ratings implications of revised programming. A new or existing cable channel may also investigate the programming image which will produce the greatest audience share or share of revenues.

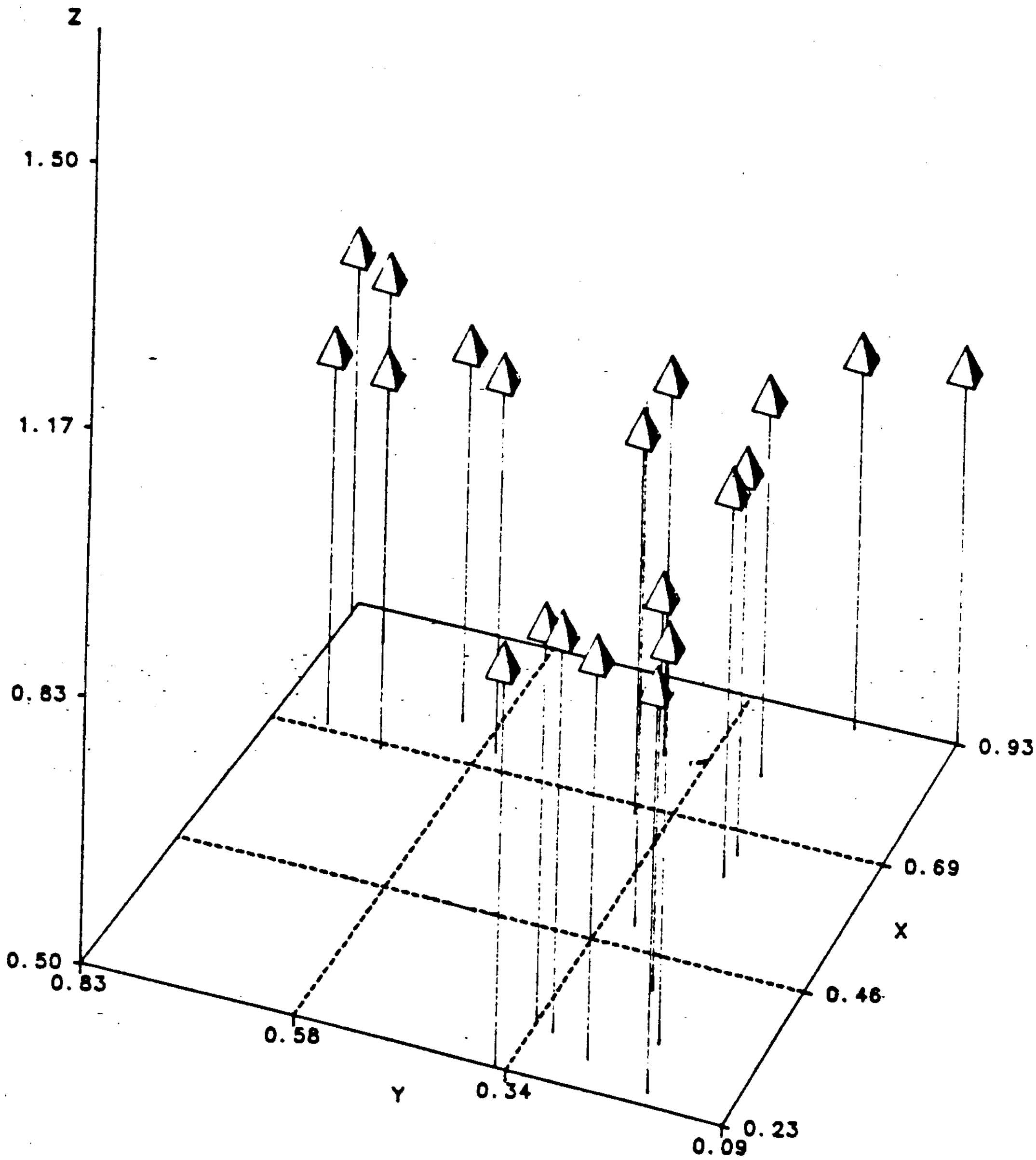
Because of the rapid increase in cable television's share of the viewing audience and cable's increasing share of television revenue, cable television programming is a dynamic decision area which is growing in importance. This chapter overviews an approach for using research to help make timely programming decisions in the rapidly evolving cable television environment.

TABLE 1

Market Share Estimation for Cable Television Channels

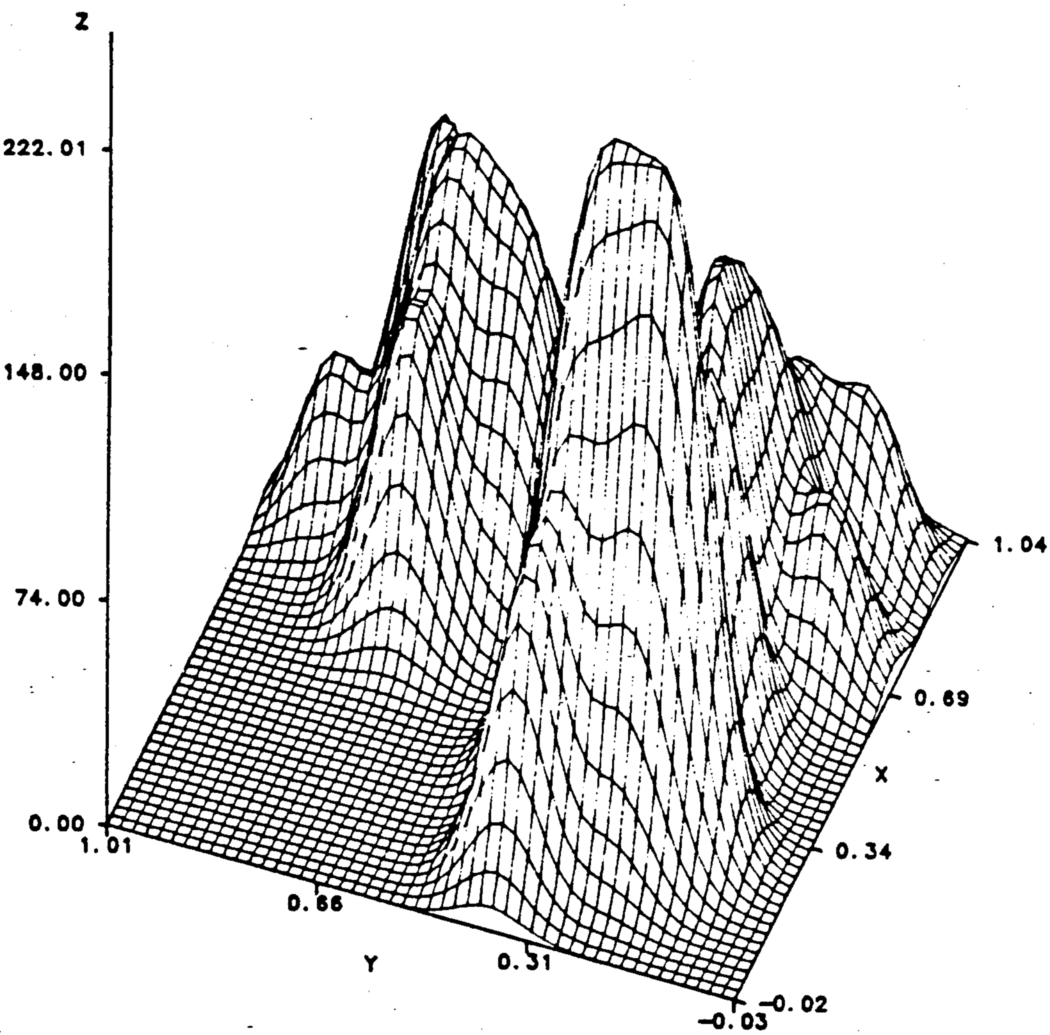
Channel Number	Channel Name	Estimated Market Share	Estimated Market Share After #15 Enters the Market
1	LIFETIME	7.65	5.62
2	ESPN	5.20	5.15
3	CNN	6.06	5.45
4	USA	3.57	3.28
5	WTBS	4.23	4.38
6	NICK	4.64	3.62
7	INDEPENDENT	2.58	2.51
8	MTV	7.09	6.94
9	DISNEY	5.59	3.87
10	CINEMAX	13.58	10.52
11	A & E	5.63	3.70
12	HBO	14.82	12.04
13	GALAVISION	7.91	6.00
14	SHOWTIME	11.26	10.64
15	NEW CHANNEL	--.--	16.26

FIGURE 1



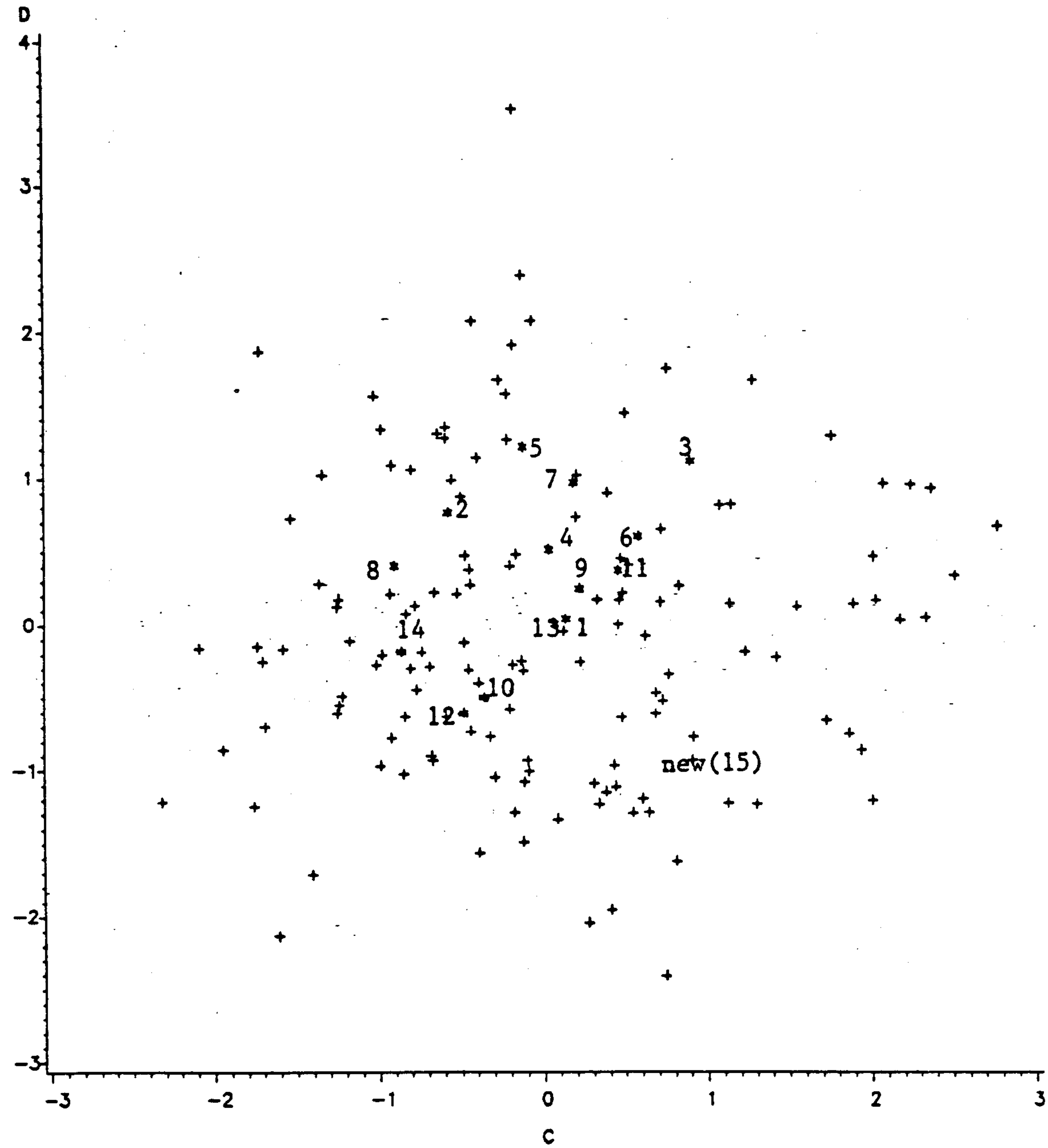
Direct Ideal Point Approach: The Density Function of the Ideal Points as Spikes at the Sample Ideal Points

FIGURE 2



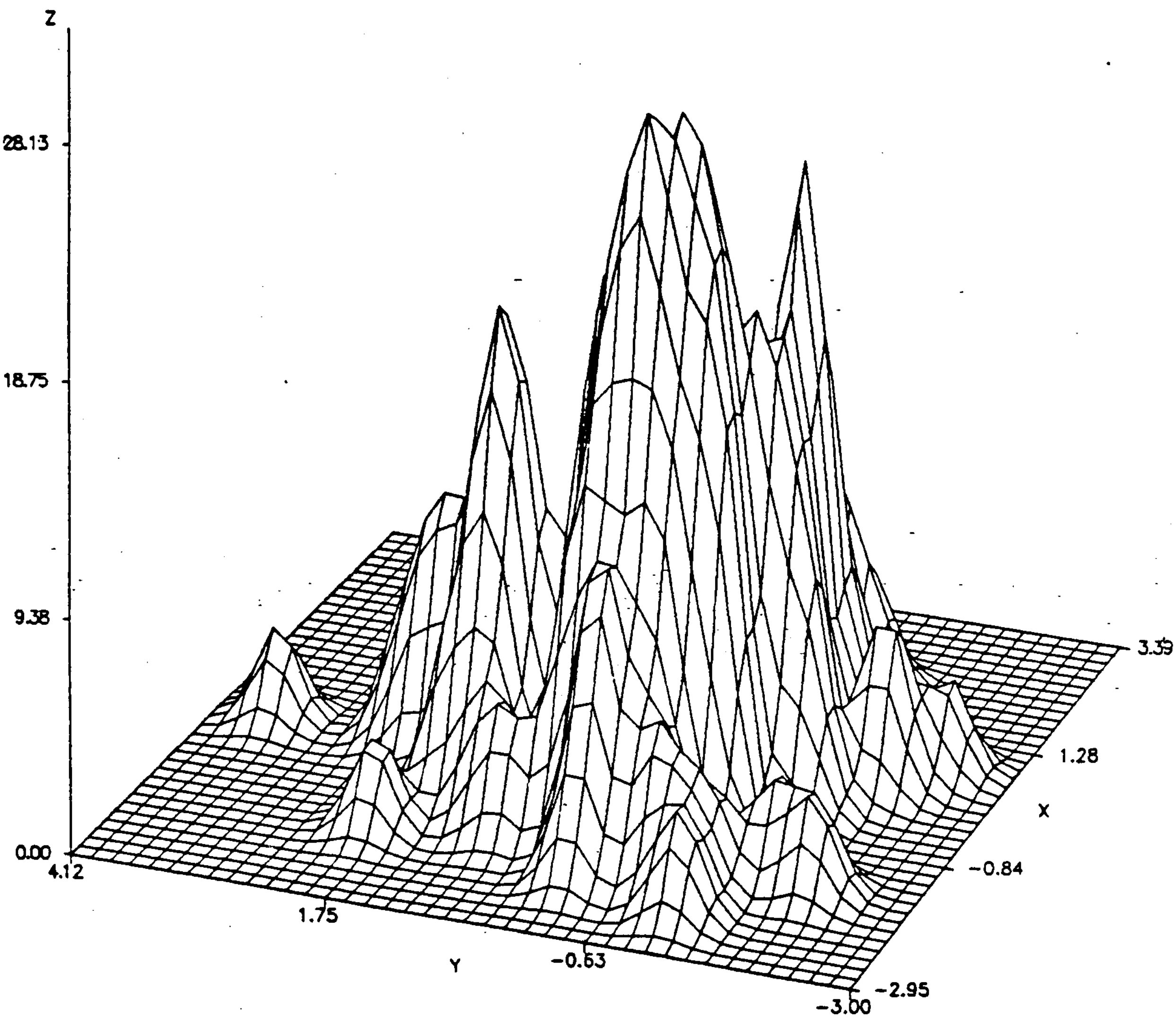
Nonparametric Density Estimation Approach: The Density Function of the Ideal Points as a Smooth Function of the Sample Ideal Points

FIGURE 3



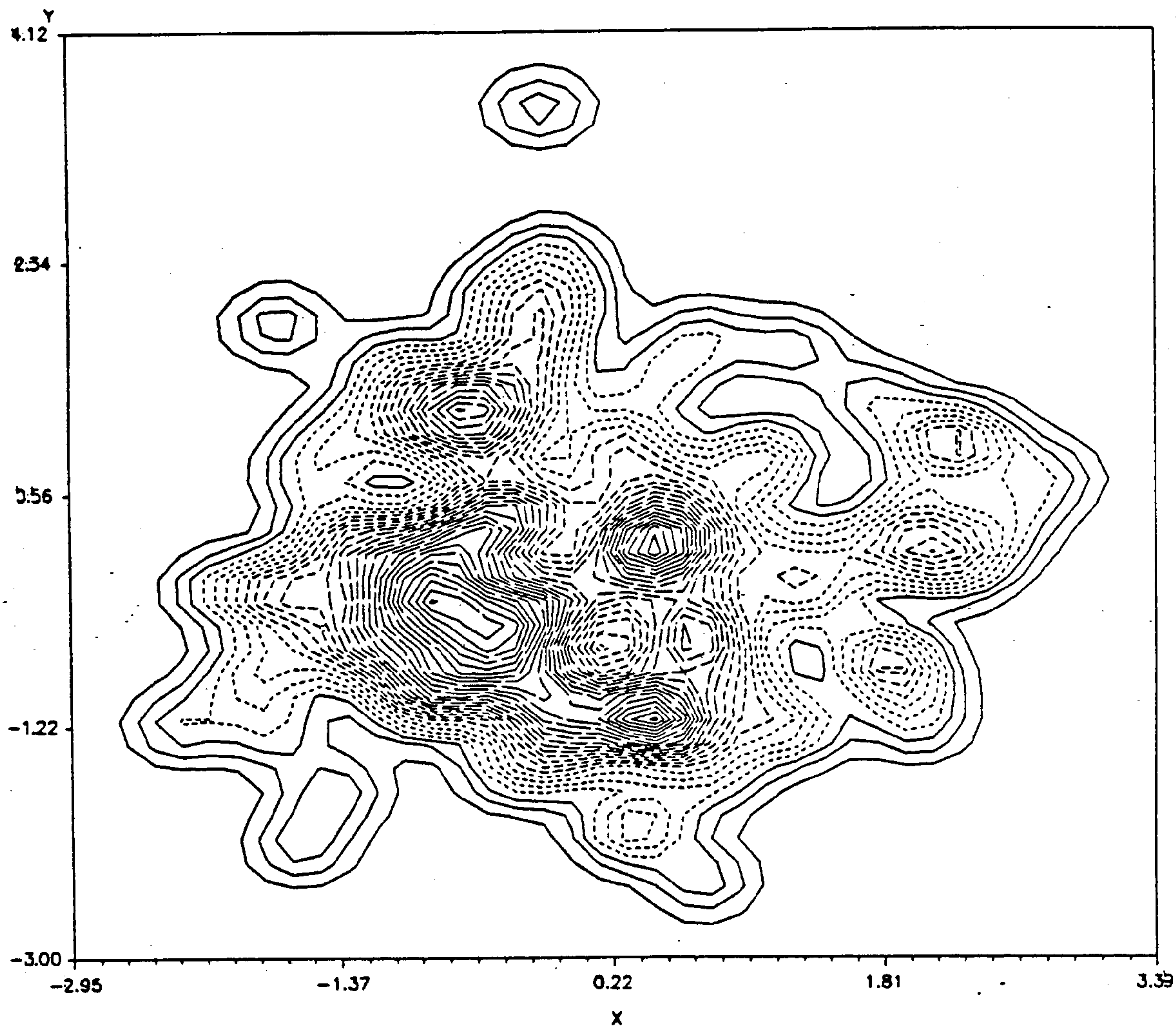
Joint Map of Ideal Points (150) and Cable Televsion Channels (14)

FIGURE 4



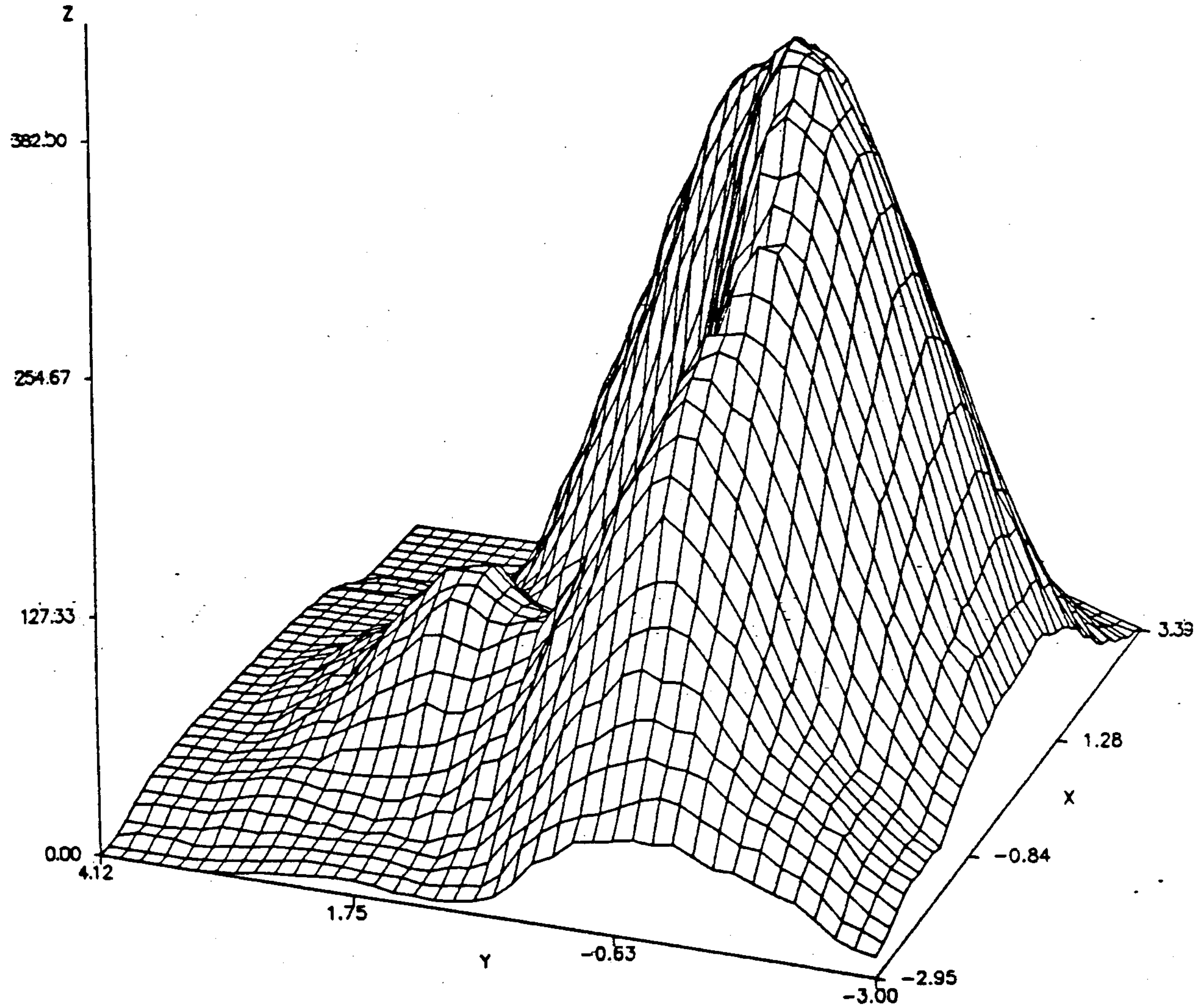
Kernel Density Map of Ideal Points

FIGURE 5



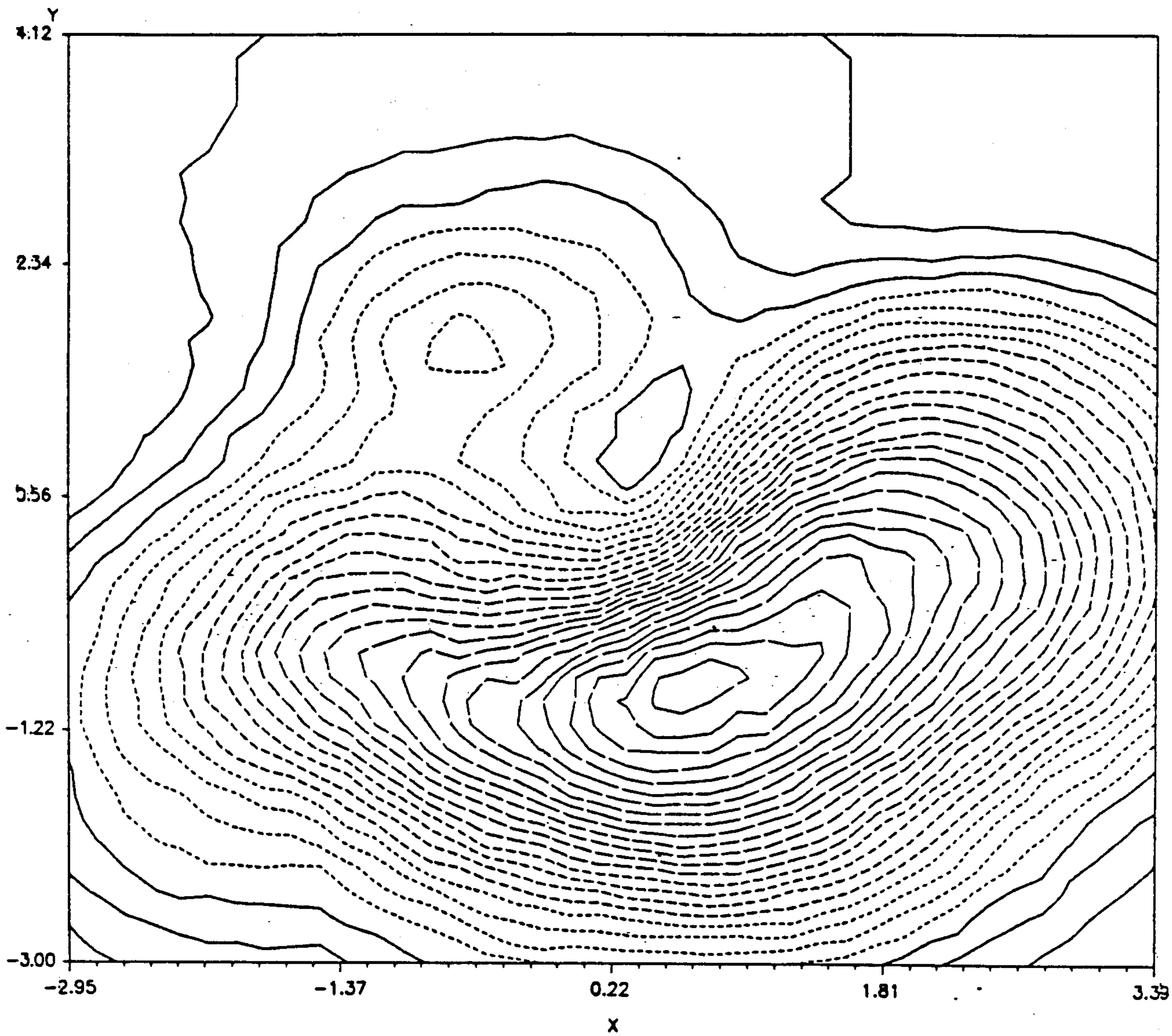
Contour Map of Density of Ideal Points

FIGURE 6



Expected Market Share for New Cable Television Channel

FIGURE 7



Contour Map of Expected Market Share for New Cable Television Channel

FIGURE 8

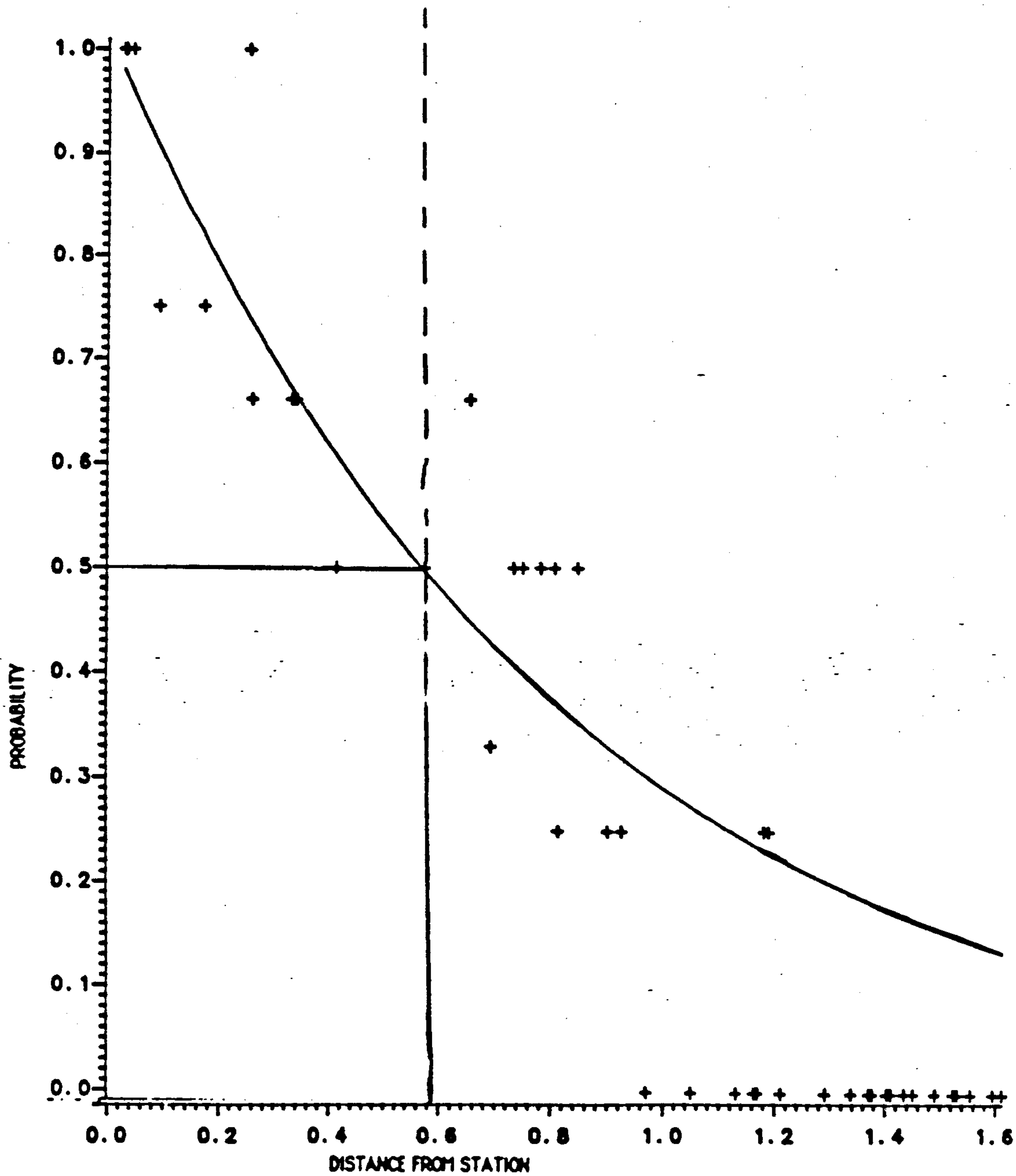


Illustration of Methodology to Determine Television Programs Associated with a Station's Location in the Perceptual Map

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