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# Viewer Preference Segmentation and Viewing Choice Models for Network Television

Roland T. Rust, Wagner A. Kamakura and Mark I. Alpert

Individual viewing decisions have a direct impact on the media planning of television advertisers and, consequently, on the revenues of the major television networks. This paper represents an attempt to better understand these decisions. We use Nielsen people meter data to build a perceptual space for programs. That space is then used to develop models explaining viewers' decision to watch television and their choice of programming. The program-choice model is a clusterwise logit model which searches for segments with similar viewing preferences. A segment-level logit model is then used to model the on-off decision. These models can be used by advertisers and advertising agencies to understand the viewing audience better, and thus to help guide their advertising media placement decisions. The models can also help television networks design programs and program schedules that are more attractive to viewers (and thus advertisers).

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# Introduction

Broadcast TV advertising revenue is approximately \$25.5 billion per year (Battaglio 1990), which explains why advertisers care so much about TV viewing. The four largest networks themselves receive \$9.383 billion per year in advertising revenue, and the largest network advertisers spend well over \$200 million per year (up to \$598.4 million in 1990 by General Motors) for network ad time (Walley 1990). The cost of a 30 second advertising spot on a popular network program such as "Roseanne" or the "Cosby Show" costs in the hundreds of thousands of dollars (Cosco 1990), depending on the audience size (rating) attained by the program and the advertising desirability of the viewers attracted.

The industry figures presented above clearly show how intertwined are the interests of the major television networks with those of the large advertisers. Both groups are affected significantly by the choice processes used by viewers in deciding whether or not to watch television, and if so, which program to choose. If there are viewer segments which make these decisions based on different preferences or tastes, it should be important to both networks and advertisers to know the composition of each segment and their particular decision processes.

The networks must care about viewer segments and viewing choice because they can use this knowledge to design more effective program schedules, and make beneficial program and schedule changes. Better programming and scheduling lead to higher ratings, and thus to more advertising revenues and higher profits.

Advertisers should also care about viewer segments and viewing choice to ensure that their advertising dollars are well-spent. Although "make-goods" (free advertising time on other programs when the scheduled advertising has been on programs which have not achieved the projected rating) are typically made available to advertisers if a program fails to attain the expected ratings, these are not always consistent with the advertisers' timing and targeting objectives. Thus, advertisers would rather "get it right the first time," to better predict viewing choice and ratings and consequently develop a more effective media schedule. This is especially a concern during the "upfront" buying period in which advertisers must guess how the networks' new Fall schedules will fare. The practical concerns of the networks and advertisers translate to three main research problems:

- 1) What is the "market structure" of viewing choice, i.e., are there distinct and identifiable viewing segments?
- 2) How do viewers (or viewing segments) decide whether to turn the TV on or off?
- 3) How do viewers (or viewing segments) choose which program to watch?

The purpose of this paper is to propose a modelling approach which begins to address these questions in a unified way. First, we build a preference map which displays the inter-relationships among television programs in terms of viewership. We use this map to identify viewer segments with distinctive preferences and to understand the preference structure within each segment. We then model each segment's decision to watch or not to watch television at any given time, an aspect that has not been considered in previous models of television viewership. These three models, used together, provide a coherent method for analyzing the viewing audience.

The remainder of the paper is organized as follows. The second section discusses previous research in structuring viewing alternatives, segmenting viewers, and modelling viewing choice. Section 3 builds a viewing space to structure the TV program alternatives. Section 4 develops and tests models for viewer segmentation and program choice; Section 5 develops and estimates a model of the on-off decision. Implications of the research are given in Section 6.

# **Previous Research**

Previous research in this area tends to take one of three forms. Research on structuring viewing alternatives attempts to explore the relationships between television programs, and to determine which programs are similar to one another. Research on viewer segmentation attempts to find groups of viewers who make similar viewing decisions. Research on viewing choice models attempts to construct models which explain and predict viewing decisions, such as which program to watch.

# Structuring Viewing Alternatives

There have been three main research approaches to structuring viewing alternatives. The easiest approach is to simply establish a program categorization scheme *a priori*, assuming that programs within a program type are similar, while program pairs across different program types are dissimilar. In this approach, one must also assume that the program types are obvious enough to be judgementaly assigned, without reliance upon data. This is the general approach used by Nielsen, which categorizes programs into one of thirty-nine program types, including such narrow categories as "conversations, colloquies," "children's news," "instructions, advice," "official police," and "sports academy." A more concise and less unwieldy categorization is used by Headen, Klompmaker and Rust (1979) and Rust and Alpert (1984). Their categorization scheme includes ten program types: serial drama, action drama, psychological drama, game show, talk or variety, movie, news, comedy, sports, and other. This streamlined categorization scheme has been shown to improve the predictive power of television viewing models (Headen, et.al. 1979; Rust and Alpert 1984). Nevertheless, a drawback of a priori categorization is that it is not directly supported empirically.

The second approach to program structuring is empirically based, and relies on factor analyzing viewing choice data. Gensch and Ranganathan (1974) found program types which were similar to the *a priori* categorizations described above. Other researchers also obtained face valid programs using factor analysis (Kirsch and Banks 1962; Wells 1969; and Frank, Becknell and Clokey 1971). However, Ehrenberg (1968) failed to uncover meaningful program types using this method. As in assignment of *a priori* program types, the underlying assumption is that homogeneous program categories exist, in which similarity is defined largely by membership in the same category.

The third approach is the viewing space approach, in which a continuous segmentation scheme is employed (Rust and Donthu 1988). Multidimensional scaling (or unfolding) is used to assign programs to locations in an n-dimensional space, usually of low dimensionality to facilitate interpretation. Rust and Donthu (1988) used this approach to map cable television networks and viewers in the same space with network television viewers. This approach does away with the discrete typology of program types. Rather, distance between programs in the space reflect program similarity. A variant of this latter approach is used in Section 3.

# Segmenting Television Viewers

As with the segmentation of television programs, the approaches used to segment viewers also rely on a priori segmentation to empirically derived segmentation. Advertisers have traditionally used demographics to form (a priori) segments of the viewing audience. This is also the approach used by Rust and Alpert (1984) in their viewing choice model. Goodhardt, Ehrenberg and Collins (1975) have done considerable exploratory empirical work using demographic segments. Psychographics have also been used to segment the viewing audience (Villani 1975). Again, the disadvantage is that a priori segmentation schemes may not produce homogeneous viewing behavior within segment.

Empirically derived segmentation schemes for television viewers implicitly assume a benefit segmentation (Haley 1968) framework. It is assumed that program content results in a benefit to the viewer, and that similar programs would supply similar benefit. Gensch and Ranganathan (1974) and Frank and Greenberg (1979) constructed viewing segments on this basis, as did Wicks (1989) for the content of network news programs and Rust and Donthu (1988) for cable television networks. The advantage of a benefit segmentation approach is that homogeneity of viewing behavior is more likely when viewing preferences are held constant. Section 4 applies a recently proposed benefit segmentation methodology (Kamakura and Russell 1989) to the problem of discovering viewer benefit segments. This approach will lead to segments that are homogeneous in terms of viewing behavior, rather than in terms of some a priori criterion such as demographic, life-style, as in previous studies.

# Viewing Choice Models

Because viewing data are difficult to obtain and work with, relatively few viewing choice models have been proposed. A thorough review is given in Rust (1986). Aggregate viewing choice models (ratings prediction models) have been proposed by Gensch and Shaman (1980), Horen (1980), and Henry and Rinne (1984). In addition, several proprietary ratings prediction models exist. Rather than focusing on aggregate ratings prediction, we instead focus on building ratings from individual or segment viewing behavior.

Individual-level viewing choice models have been proposed by Lehmann (1971), Darmon (1976), and Zufryden (1973). Darmon's model is interesting in that it incorporates channel loyalty as a predictor of choice, thus foreshadowing the development of audience flow models. Zufryden also captures dynamics through use of a linear learning model formulation.

A more comprehensive viewing choice model was

recently proposed by Rust and Alpert (1984). Their model assumes a Luce (1959) choice rule, with utilities for programs dependent upon (a priori) segment preference for (a priori) program type, and audience flow. "Audience flow" refers to whether the TV set was previously on or off, whether it was tuned to the same channel as the program option, and whether the program is starting or continuing. They found that audience flow was very important to viewing choice, and, thus, that a straightforward approach to viewing choice is incomplete. The viewing choice model proposed in Section 4 also incorporates audience flow.

In summary, many approaches can be found in the literature for structuring viewing alternatives, segmenting the TV viewing market, and modeling viewing choice. Our approach offers several advantages over these previous attempts. First, it combines all three stages (defining the viewing space, segmenting the market and modeling choice) into an integrated model. Second, it simultaneously identifies preference segments and estimates their preference function. Third, it acknowledges the possibility of heterogeneity in preferences that go beyond simple sociodemographic differences. Finally, our approach considers the decision to watch or not watch television along with the choice of program.

# **The Viewing Space**

To build effective models of viewing choice, we first need to supply a basis for defining TV program alternatives along determinant dimensions of viewers' choice. As discussed in the previous section, the commonly used *a priori* categorizations are often limited to a few typologies, based on somewhat arbitrary judgements. In this section, we build a model for the definition of the viewing space, and estimate it using Nielsen people meter viewing choice data.

## The Model

Similar to Rust and Donthu (1988), we assume that the network programs can be positioned along a continuous underlying characteristic-space which can provide a parsimonious characterization of each program in terms of its relationship to all other programming options. The location of these programs is determined empirically, so that programs that are viewed by the same audience are located closer to each other than programs that do not share a common audience. Therefore, programs that appeal to the same "tastes" or preferences will be shown to-

gether in the final map. Thus, we are basing our map on similarity of choices, and (by extension) preferences. Our approach is to map programs in space, according to similarity of choice patterns, using multidimensional scaling. It is important to note that a preference space may be fundamentally different from a perceptual space, even though the methodology producing them may be substantially the same. For example, due partly to variety seeking or complementarity, individuals may "prefer together" dissimilar programs. (Consider, for example, coffee and cream which are quite dissimilar but "preferred together" and thus mapped as "similar"). Constructing an appropriate measure of similarity between programs requires some care, because some programs have high ratings while others have low ratings. Thus, simple similarity measures, such as the size of the joint audience, may be contaminated by size effects. We use a measure of similarity which adjusts for size effects. Adapting Goodhardt and Ehrenberg (1969), we let

# (1) $\mathbf{S}_{ij} = \mathbf{r}_{ij}/\mathbf{r}_i\mathbf{r}_j$

where  $S_{ij}$  is a measure of similarity,  $r_{ij}$  is the joint audience (in proportional terms) of programs i and j, and  $r_i$  and  $r_j$  are the proportional ratings of programs i and j respectively. Note that if exposure to i and exposure to j are statistically independent (in the aggregate), then  $S_{ij}$  will be one, within sampling error. The numerator can be viewed as a joint probability of choosing both programs, with the denominator being the product of the marginal probabilities. Thus,  $S_{ij}$  is a measure of how much bigger or smaller than expected by chance the joint audience is, adjusting for the audience sizes of the two programs.

To avoid bias from audience flow (e.g., Program A directly follows Program B in time), we consider only pairs of programs from different days. This does not eliminate *all* audience flow effects, because "second-order" effects may still exist. For example, if Program A directly follows Program B (on the same channel) on Tuesday, and Program C is on Friday, then Programs A and B will have high similarity  $S_{AB}$ , because their duplication with Program C will be similar. However, the first-order effects (A being similar to B because one follows the other in the same channel) *will* be eliminated.

# Data

We used people meter individual-level television viewing data collected by the A.C. Nielsen Company. Our data consisted of 11,501 individual viewing histories, from 4,177 households from one week in January, 1988 (this narrow sampling interval may create potential seasonal bias in the results, easily eliminated with a longer sampling period, not available to us at the moment). These data included each individual's viewing (ABC, CBS, NBC, Fox, cable/ other, or don't view) for each quarter hour. We analyzed data from all seven days of the week for all time slots in prime time (8 PM to 11 PM). The data were obtained from a national probability sample.

Programs on the TV were automatically recorded by a meter. Individual viewers punched in and out whenever they left the room, resulting in individual viewing records. Although there have been concerns expressed in the television industry concerning measurement of "out of home" viewers (Walley 1990) and inexplicable rating declines (Graham 1989), the Nielsen people meter data remain the industry standard for setting television advertising rates.

Our empirical analyses were performed on three sub-samples of 600 individuals, drawn randomly from the 11,501. The first sub-sample was used to estimate the viewing choice model. The second subsample was used to perform a test-retest reliability check of the viewing choice model, and the third subsample was used to perform predictive validity checks of the viewing choice model.

# Results

We produced multidimensional scaling maps using S<sub>ii</sub> as a similarity measure for seventy prime time programs (see Table 1), using the ALSCAL non-metric MDS procedure in SPSS-X. A considerable improvement in fit was attained moving from a twodimensional to a three-dimensional space (improvement in stress from .262 to .174 and  $R^2$  from .662 to .764). Since the improvement obtained with a 4-dimensional solution was substantially smaller, and because of the obvious difficulty in visualization, we selected the three-dimensional solution, shown in Figures 1 and 2, with a key for the program abbreviations given in Table 1. The first two dimensions (Figure 1) show much about how the programs group together. It is clear from the map that two influences strongly affect the clustering of programs. First, programs of similar content tend to group together. For example, the upper left quadrant seems to be predominantly comedies ("Bill Cosby," "Roseanne," "Cheers"), while the upper right quadrant appears to be dominated by serials and mysteries ("Falcon Crest," "Murder She Wrote," "Dallas"). By contrast, action

# March 1992

| Abbreviation | Program                        | Network    |
|--------------|--------------------------------|------------|
| ADIFF        | A Different World              | NBC        |
| ABCMON       | ABC Monday Night Movie         | ABC        |
| ABCSAT       | ABC Saturday Night Movie       | ABC        |
| ABCSUN       | ABC Sunday Night Movie         | ABC        |
| ALF          | Alf                            | NBC        |
| ALMOST       | Almost Grown                   | CBS        |
| AMEN         | Amen                           | NBC        |
| AMERIC       | America's Most Wanted          | FOX        |
| BEAUTY       | Beauty & the Beast             | CBS        |
| BILLCO       | Bill Cosby Show                | NBC        |
| CBSSUN       | CBS Sunday Night Movie         | CBS        |
| CBSTUE       | CBS Tuesday Movie              | CBS        |
| CHEEBS       | Cheers                         | NBC        |
| CHINAB       | China Beach                    | ABC        |
| DALLAS       | Dallas                         | CBS        |
| DAVIDH       | David Hartman - Early Warning  | Eox        |
|              | David Harman - Lany Warning    | NBC        |
|              | Door John                      | NBC        |
| DESIGN       | Designing Women                |            |
|              | Designing Women                | CBS        |
|              | Dirty Dancing                  | CBS<br>Fau |
| DVNAST       | Duel                           | FUX        |
|              | Dynasiy<br>Emoty Neet          | ABC        |
|              | Emply Nest                     | NBC        |
|              |                                | CBS        |
|              | Family hes                     | NBC        |
| FURITE       |                                | CBS        |
|              |                                | ABC        |
|              | Garry Shandling Show           | Fox        |
| GOLDEN       | Golden Girls                   | NBC        |
| GROWI        | Growing Pains                  | ABC        |
| HEARIB       | Heartbeat                      | ABC        |
| HOGANF       | Hogan Family 7                 | NBC        |
| HOOPER       | Hooperman                      | ABC        |
| HUNTER       | Hunter                         | NBC        |
| INTHEH       | In the Heat of the Night       | NBC        |
| JUSTTH       | Just the Ten of Us             | ABC        |
| KATEAN       | Kate & Allie                   | CBS        |
| KNIGHT       | Knightwatch                    | ABC        |
| KNOTSL       | Knot's Landing                 | CBS        |
| LALAW        | LA Law                         | NBC        |
| MACGYU       | MacGyver                       | ABC        |
| MAGICB       | Magical World - Disney Special | NBC        |
| MARRI        | Married With Children          | Fox        |
| MATLOC       | Matlock                        | NBC        |
| MIAMI        | Miami Vice                     | NBC        |
| MIAMI2       | Miami Vice Special             | NBC        |
| MIDNIGHT     | Midnight Caller                | NBC        |
| MISSIO       | Mission: Impossible            | ABC        |
|              |                                | continued  |

Table 1Key to Program Abbreviations on Viewing Space Map

| Abbreviation | Program                | Network |
|--------------|------------------------|---------|
| MISTER       | Mr. Belvedere          | ABC     |
| MOONLI       | Moonlighting           | ABC     |
| MURDER       | Murder, She Wrote      | CBS     |
| MURPHY       | Murphy's Law           | ABC     |
| MURPHY       | Murphy Brown           | CBS     |
| NBCMON       | NBC Monday Night Movie | NBC     |
| NBCSUN       | NBC Sunday Night Movie | NBC     |
| NEWHART      | Newhart                | CBS     |
| PARADI       | Paradise               | CBS     |
| PERFEC       | Perfect Strangers      | ABC     |
| REPORT       | Reporters              | FOX     |
| ROSEAN       | Roseanne               | ABC     |
| TELEVI       | TV 101                 | CBS     |
| THIRTY       | Thirtysomething        | ABC     |
| TOUROF       | Tour of Duty           | CBS     |
| TRACEY       | Tracy Ullman Show      | Fox     |
| TWENTY       | 20/20                  | ABC     |
| TWOTWO       | 227                    | NBC     |
| UNSOLV       | Unsolved Mysteries     | NBC     |
| WESTFI       | West 57th              | CBS     |
| WHOST        | Who's the Boss         | ABC     |
| WONDER       | Wonder Years           | ABC     |

Table 1, Continued

programs cluster in the middle right ("Miami Vice," "MacGyver," "Tour of Duty").

The other main influence which seems to be operating is a network effect. For example, the comedy programs seem to split into two clusters, one mostly ABC ("Perfect Strangers," "Full House," "Moonlighting") and the other mostly CBS and NBC ("Murphy Brown," "Bill Cosby," "Designing Women"). Also notable is that the program type concept does not seem to be perfectly borne out by these data. For example, the Yuppie slice of life dramatic series, "Thirty Something," positions with the comedies, as does "LA Law," and the "Magical World" Disney special positions with the serials and mysteries.

The coordinates for each programming option in this three-dimensional space define the relative position of the programs in terms of their direct competition for common audiences. These coordinates are continuous descriptors to be used as one of the determinants of choice in our preference-segmentation model (to be described next).

# **Segmentation and Program Choice**

The viewing space constructed in the previous section provides a basis for segmenting viewers and explaining viewing choice. From prior research, we also know that audience flow, e.g., whether a program is on the same channel which was viewed in the previous time period, must also be included in any sensible viewing choice model. We first build a model of program choice, given that the television is on.

# The Model

Our model assumes that homogeneous viewing segments exist, or at least that aggregating individuals into homogeneous segments is a reasonable simplifying approximation. We also assume that programming preferences by each segment can be represented as ideal points located in the viewing space (described in the previous section), and that viewers in a segment will tend to choose programs which are near the segment's ideal point, all other things being equal. We allow the possibility of anti-ideal points, in which viewers in a segment will tend to choose programs which are as far away as possible from these locations. In other words, if an ideal point is found, then the individual will tend to choose programs as close to the ideal point as possible, while if an anti-ideal point is found, the individual will tend to avoid programs close to the anti-ideal point. Ideal points would provide information about the most prefered combination of characteristics in TV programs, while anti-





Figure 1 3-Dimensional Viewing Space - Dimensions 1 and 2



Figure 2 3-Dimensional Viewing Space - Dimensions 1 and 3

ideal points would only provide information about what should be avoided in designing a new program. Put in mathematical terms, the inherent utility (disutility) of a program to a particular segment is represented by the distance between the program's location in the viewing space and the segment's (antiideal) point.

To incorporate audience flow (Rust and Alpert 1984), we assume that whether the program is on the channel which was previously viewed also has an effect on utility. In other words, we allow for the possibility of viewership inertia; a program in the same channel viewed previously could have an advantage over programs in competing channels, due to this inertia. In addition, because cable TV and other non-network viewing options have proliferated in recent years (Krugman and Rust 1987), and non-network choice is included in the data set, we also include in the model the attractiveness of non-network viewing for each segment, which would account for the segment's propensity to watch non-network programming.

In accordance to classic random utility theory, we assume that at any time, viewers choose the program with the highest utility. The utility of a program option to an individual belonging to a particular segment s is as follows:

(2) 
$$U_{is} = \sum \Theta_{ks} (X_{ik} - \mu_{ks})^2 + C_{1S} (LAST_i) + C_{2S} (CABLE_i) + \varepsilon$$

where

| U <sub>js</sub>  | = | utility of program j to members of segment s  |
|------------------|---|---|
|                  |   | (suppressing time subscripts throughout)  |
| $\Theta_{ks}$    | = | logit coefficient corresponding to dimension k for<br>segment s   |
| X <sub>jk</sub>  | = | location of program j in dimension k in the view-<br>ing space  |
| μ <sub>ks</sub>  | = | segment s ideal point (or anti-ideal point) loca-   |
|                  |   | tion in dimension k   |
| $C_{1S}, C_{2S}$ | = | logit coefficients for segment s  |
| LAST             | = | 1 if program j is on the network channel previ-<br>ously seen by the viewer, or 0 otherwise.  |
| CABLEi           | = | 1 if option j is non-network or 0 otherwise.  |
| ε                | = | an error term, assumed distributed extreme<br>value, which accounts for the stochastic nature<br>of choice behavior and other random sources of |
|                  |   |   |

The first utility component in Eq.2  $(\sum_{k} \Theta_{ks} (X_{jk} - \mu_{ks})^2)$  contains the weighted (by  $\Theta_{ks}$ ) distance between the program j (represented by the location  $X_{jk}$ ) and the segment's ideal point  $(\mu_{ks})$ . Note that if  $\Theta_{ks}$  is positive, the utility for a particular program j decreases as it moves closer to the segment's ideal point  $(\mu_{ks})$ , and thus,  $\mu_{ks}$  is an anti-ideal point. If  $\Theta_{ks}$  is negative, then utility decreases with distance, and thus,  $\mu_{ks}$  is an ideal point.

Unfortunately, the data available to us collapse all non-network viewing into one category, making it impossible to pinpoint non-network program locations (i.e., the  $X_{jk}$ 's are known only for network programs). Thus, the CABLE<sub>j</sub> coefficient,  $C_{1S}$ , is in some sense, a proxy for the average viewing space utility which would be anticipated from the best non-network option. Consequently, only the two last components of utility ( $C_{1S}$ (LAST<sub>j</sub>) and  $C_{2S}$ (CABLE<sub>j</sub>)) are defined for non-network programs.

The utility formulation in Eq.2 permits estimation of a clusterwise logit model (Kamakura and Russell 1989; Kamakura and Mazzon 1991). In this model, the conditional probability of choosing program j, given that the viewer belongs to segment s is:

(3) 
$$P_{js} = \exp(U_{js}) / \sum_{j} \exp(U_{j's}).$$

Equation 3 shows the probability that a viewer chooses program j, conditional on the information that she belongs to segment s. The unconditional choice probability for a viewer randomly drawn from the population of TV viewers will be given by,

(4)  $P_j = \sum_{s} f_s P_{js}$ ,

where  $f_s$  is the relative size of segment s (i.e., the probability that a viewer randomly drawn from the population will be a member of segment s).

The clusterwise logit model briefly described in the previous equations (and in more detail by Kamakura and Russell 1989) allows us to identify viewer segments that contain relatively homogeneous groups of viewers in terms of programming preferences and viewership patterns, to estimate the utility function for each segment, and to estimate the relative size of these segments in the TV viewing population. In essence, our model permits each viewing segment to have different viewing preferences and to have different tendencies to continue watching the same channel or to prefer cable and non-network programming.

# Estimation

We estimated the model on a sub-sample of 600 viewers, using 9,785 total viewing choice occasions (details about the maximum-likelihood estimation of the clusterwise logit model can be found in Kamakura and Russell 1989). Estimation of the clusterwise logit model resulted in three segments of approximately equal size. Estimated parameters and standard errors are shown in Table 2.

|                                |              | Coefficient (Standard Error) |               |  |  |  |
|--------------------------------|--------------|------------------------------|---------------|--|--|--|
| Variable                       | Segment A    | Segment B                    | Segment C     |  |  |  |
|                                | (Easterners) | (Westerners)                 | (Southerners) |  |  |  |
| Θ                              | .244 (.042)  | .450 (.050)                  | .232 (.051)   |  |  |  |
| $\Theta_{v}^{n}$               | .478 (.040)  | .467 (.044)                  | .261 (.039)   |  |  |  |
| $\Theta_{\mathbf{z}}^{\prime}$ | .221 (.053)  | .456 (.065)                  | .155 (.053)   |  |  |  |
| μχ                             | .515 (.084)  | .955 (.069)                  | 010 (.114)    |  |  |  |
| μ <sub>v</sub>                 | 773 (.052)   | 844 (.088)                   | 841 (.084)    |  |  |  |
| $\mu_{7}$                      | 030 (.101)   | 364 (.048)                   | 097 (.149)    |  |  |  |
| LÃST                           | 2.396 (.078) | 1.937 (.089)                 | 1.724 (.069)  |  |  |  |
| CABLE                          | 2.276 (.114) | 1.393 (.172)                 | .296 (.135)   |  |  |  |
| Est.Segment Size               | .343 (.055)  | .329 (.055)                  | .329 (.055)   |  |  |  |

 Table 2

 Estimation Sample: Clusterwise Logit Results for Viewing Choice Model

Chi-Square= 19,728.5 (26 d.f.)

For all segments, our results indicate anti-ideal points in the viewing space; all estimated weights for the three dimensions in the viewing space are positive and statistically significant (at 0.01 level), indicating that the farther a program is from the idealpoint for a given segment, the highest its utility will be for that segment (note that this result was determined by the data, rather than pre-specified in our model).

The results in Table 2 also indicate that segment A has the greatest inertia (largest coefficient for LAST<sub>j</sub>); all other factors being equal, members of segment A are more likely to continue watching the same network channel, suggesting the now common strategy of "anchor" shows at the very beginning of the primetime period. Members of segment A also have the greatest propensity to view non-network programming (largest coefficient for CABLE<sub>j</sub>). Segment C has the least tendency to stay with the same network channel, and also the least tendency to view nonnetwork programming.

Figures 3, 4, and 5 show the anti-ideal point locations for segments A, B and C respectively, superimposed on the viewing space and program locations. Isoutility contours are also shown. An isoutility contour shows a line on which preference is the same. In other words, if two different programs were at different points on the line, then they would be preferred equally. We see, for example, that all segments seem to avoid action programs, although the tendency is less pronounced for segment C. Segments A and B are positioned fairly similarly in the viewing space, which implies that other variables, such as segment A's tendency to prefer non-network programming, may provide the major differences between those segments.

#### Segment Descriptions

Now that viewers have been grouped into segments of distinct preferences and viewership patterns, it would be useful to find out whether there are any other differences among these segments aside from TV viewership. We investigated the composition of the viewing segments, using a variety of socio-demographic variables. We were especially interested in whether the segments corresponded in any simple way to the demographic classifications commonly used in the industry. We tested for significant differences in composition, using chi-square tests, based on geographical region, city size, household income, age, household size, education, presence of small children, and cable subscription. All descriptor variables resulted in significant differences at the .05 level.

Table 3 summarizes the descriptions of the three segments. We see that segment A, the segment with the highest inertia and preference for non-network programming, tended to concentrate in the Eastern states, were older, from small households, and heavy cable subscribers. Segment B tended to be more Western, urban, wealthy, younger, from large households, well-educated, and to have more small children. Segment C tended to be more Southern, rural, less wealthy, less educated, have few small children, and not watch much cable. We will refer to the segments as "Eastern," "Western," and Southern," although it is clear that these variables (and other variables) reflect only statistical tendencies. None of the descriptor variables (including geography) in isola-







| Variable          | Segment A<br>(Easterners) |         | Segment B<br>(Westerners) |        | Segment C<br>(Southerners) |         |
|-------------------|---------------------------|---------|---------------------------|--------|----------------------------|---------|
|                   |                           |         |                           |        |                            |         |
| Geography         | Eastern                   | (1.26)* | Western                   | (1.19) | Southern                   | (1.23)  |
| County Size       | -                         | -       | Large                     | (1.28) | Small                      | (1.30)  |
| Income            |                           | -       | >40K                      | (1.29) | <15K                       | (1.20)  |
| Age               | 55+yrs                    | (1.16)  | 18-34                     | (1.31) | _                          |         |
| Household<br>Size | 2                         | (1.30)  | 4+                        | (1.39) | _                          |         |
| Education         | _                         |         | College                   | (1.22) | 0-8 yrs                    | (1.47)  |
| Children<br>>3yrs |                           | -       | Kids                      | (1.37) | Kids                       | (.69)   |
| Cable TV          | Pay+Basic (1.51)          |         | _                         | -      | Pay+Basi                   | c (.42) |

Table 3 **Characteristics of Viewing Segments (Index)** 

Table 4 **Retest Sample: Clusterwise Logit Results for Viewing Choice Model** 

|                                    |             | Coefficient (S | Standard Error) |               |  |
|------------------------------------|-------------|----------------|-----------------|---------------|--|
| Variable                           | Segment A   | A Segr         | ment B          | Segment C     |  |
|                                    | (Easterners | s) (Wes        | terners)        | (Southerners) |  |
| $\overline{\Theta_{\mathbf{Y}}}$   | .304 (.044  | 4) .433        | (.046)          | .223 (.051)   |  |
| $\Theta_{v}^{2}$                   | .512 (.042  | 2) .427        | (.042)          | .247 (.044)   |  |
| $\Theta_{\mathbf{z}}^{\mathbf{y}}$ | .243 (.053  | 3) .321        | (.052)          | .219 (.056)   |  |
| μ,                                 | .372 (.065  | 5) .811        | (.049)          | .181 (.128)   |  |
| $\mu_{V}$                          | 630 (.050   | ))781          | (.055)          | .998 (.092)   |  |
| μ <sub>z</sub>                     | 093 (.097   | 7)349          | (.068)          | .035 (.101)   |  |
| LÂST                               | 2.265 (.085 | 5) 1.906       | (.075) 1        | .571 (.082)   |  |
| CABLE                              | 2.459 (.112 | 2) 1.190       | (.134)          | .456 (.153)   |  |
| Est.Segment Size                   | .302 (.078  | 3) .420        | (.078)          | .456 (.153)   |  |

Chi-Square 20,162 (26 d.f.)

tion are really strong indicators of segment membership.

# **Reliability and Validity**

In order to ascertain that our results were not mere random "accidents," we investigated the test-retest reliability of the clusterwise logit estimation by reestimating the model on a new random sample. The results are given in Table 4. Again, three segments were obtained, and, again, anti-ideal points were found for all segments. The segment anti-ideal points and coefficients match up well with the original segments (almost always within sampling error), but the estimated related segment sizes are somewhat different, but again are within sampling error. We thus conclude that the estimation appears to be relatively stable across the two cases.

We also conducted a test of the predictive validity of the model. We used a holdout sample of 600 individuals, and predicted their program choice histories, one at a time, using the model estimated on the original estimation sample (Table 2). To avoid giving our model an unfair advantage, we simply used the relative segment sizes as prior probabilities of segment membership, and did not update those probabilities. This resulted in a extremely conservative test for the model, because each individual's choices are predicted based on what the model would predict for the modal response across the population.

Nevertheless, the model performed quite well. Based on 9,852 choice occasions, a naive model which assumes continuing to view the same channel, or choosing randomly otherwise, chose correctly 4,628 times, for an average of 46.4%. Simple inertial models have been shown to predict almost as well as more sophisticated models (Rust and Alpert 1984), so the clusterwise logit aggregate model's predictive improvement to 5,266 correct (53.5%) is notable. Given enough history to update confidently the segment priors, one would anticipate that further predictive improvement might occur.

# **Modelling the On-Off Decision**

Some television network executives have long maintained that viewing is a two-stage process. First, the viewer decides to watch TV, and only then does he/she choose what to watch. In fact, there is indirect evidence that this two-stage model may be correct. Gensch and Shaman (1980) found that network TV viewing was highly predictable using a seasonal time series model, thus implying that network programming has little ability to persuade households to turnon their TV sets.

The opposite point of view holds that individuals turn on the TV specifically to watch a particular program, implying that network programming would have a direct impact on the number of households watching television at any given time.

Therefore, there is some disagreement over what comes first: the decision to watch or not watch TV, or the choice of programming. Our model formulation permits the investigation of questions such as this, at any point in time.

## The Model

We develop a binary logit model to predict the on/ off decision. We assume that the attractiveness or utility of TV viewing depends on the attractiveness of the best available program, and other inertia and time-related factors. Time dummy variables are included to reflect the fact that people are more likely to go to bed as it gets late. These dummy variables permit the utility of a program for members of a given segment to be lower if it is shown at a later hour. In other words, a program has to be "really good" to keep a viewer up late. We also include a weekend dummy variable, to reflect the fact that some segments may be more or less inclined to watch TV on the weekend. We include the utility (based on the segments' ideal points) for the best available program, to test whether programming affects the decision to turn the TV on or off. We capture viewing inertia with variables which reflect whether the TV was previously on and whether the viewer was watching a show still in progress.

The utility function for TV viewing at a particular prime-time period t is described by:

(5)  $U_t = \alpha + \sum_{h=1}^{5} \beta_h D_h + \gamma_1 IWEEK_t + \gamma_2 UMAX_t + \gamma_3 ILAST_t + \gamma_4 ICONT_t + \varepsilon$ 

where

| U <sub>t</sub> =     | utility of having the television on (utility of<br>"off" is arbitrarily set to zero with no loss of<br>generality)   |
|----------------------|--|
| α =                  | intercept  |
| D <sub>h</sub> =     | 1 if viewing decision is at prime-time slot h or 0 otherwise   |
| IWEEK, =             | 1 if time period t is in a weekend or 0 if during<br>the week  |
| UMAX <sub>t</sub> =  | maximum program utility at time t, of all pro-<br>gram options. This is computed by applying<br>the utility function from the program choice<br>model (Eq.2), using only the program locations<br>and segment ideal point. |
| ILAST <sub>t</sub> : | 1 if TV was on in the previous time period, or 0<br>if previously off  |
| ICONT <sub>t</sub> : | <ul> <li>1 if the show watched in previous time period<br/>(if any) is continuing, or 0 otherwise β's, γ's are<br/>coefficients ε is random error (assumed i.i.d<br/>extreme value)</li> </ul>                             |
| A separa             | te binary logit model was estimated for  |

A separate binary logit model was estimated for each of the three segments (with 208, 198 and 194 viewers, respectively) in our validation sample. For each viewer, we used the 42 "tune in/out" decisions made in half-hour intervals during the sampling week.

#### Results

Results from the on-off logit models for each viewing segment are given in Table 5. Some interesting conclusions can be drawn from these results. For example, the coefficients ( $\beta$ 's) for the time dummies are highly significant, and show the expected decline in propensity to watch TV as it gets later in the night. These propensities (which no longer include the effects of the other variables in the model) are calculated as  $\exp(\beta_3)$ , and are shown (relative to 8:30 viewership) in Figure 6. One can also see that, all else being constant, the "tuning out" pattern of the "Westerners" is different from the other two segments.

The weekend variable, IWEEK<sub>t</sub>, is significant only for the "Westerners," who tend to watch TV less on the weekend. As expected, the inertia variables, ILAST<sub>t</sub> and ICONT<sub>t</sub>, are highly significant, indicating that all three segments are more likely to watch television at a given time t if they have been doing so in the previous time period (ILAST<sub>t</sub>), and if they were watching a program to be continued in the current period (ICONT<sub>t</sub>). A direct comparison of the coefficients for these two inertia variables ( $\gamma_3$  and  $\gamma_4$ ) leads to another interesting conclusion: the decision to watch television at any time t is more affected by the fact that the viewer was watching any channel in the previous period ( $\gamma_3$ ), than by the fact that the program watched in the previous period is in progress at

|                    |              | Coefficient (Standard Error) |               |
|--------------------|--------------|------------------------------|---------------|
| Variable           | Segment A    | Segment B                    | Segment C     |
|                    | (Easterners) | (Westerners)                 | (Southerners) |
| Intercept          | -2.44 (.13)  | -2.45 (.11)                  | -2.38 (.14)   |
| D1(8:30)           | 3.14 (.14)   | 2.80 (.12)                   | 2.84 (.15)    |
| D2(9:00)           | 1.05 (.13)   | .82 (.13)                    | .94 (.15)     |
| D3(9:30)           | 1.03 (.13)   | .55 (.13)                    | .91 (.15)     |
| D4(10:00)          | .76 (.13)    | .41 (.13)                    | .61 (.15)     |
| D5(10:30)          | .26 (.13)    | .17 (.13)                    | .24 (.15)     |
| IWEEK              | 02* (.07)    | 19 (.06)                     | 02* (.07)     |
| UMAX**             | .06* (.11)   | .16 (.07)                    | .02* (.14)    |
| ILAST              | 3.96 (.08)   | 3.61 (.07)                   | 3.84 (.08)    |
| ICONT              | .88 (.16)    | 78 (.14)                     | 1.05 (.17)    |
| Chi-Square (10 df) | 174.73       | 4460.96                      | 4332.36       |

 Table 5

 Logit Coefficients for On-Off Model

\* Not significant at .05 level.

time t  $(\gamma_4)$ ! This result lends support to the idea that most people watch *television*, rather than the actual programs.

The coefficient for  $UMAX_t$  (i.e., the influence of the programming options in the decision to watch TV) is significant only for the "Westerners" segment. They are the only segment for which we have evidence of tuning in because of program content. For the other two segments, program content does not seem to have any bearing on their decision to watch television, once again supporting the hypothesis that these viewers first decide to turn on their TV sets, and then choose among the available alternatives.

#### Discussion

We have presented a new modelling approach for investigating the viewing audience. This approach is based on a three-stage modelling procedure. In the first stage, the programs are mapped in a multidimensional viewer preference space. In this space, programs which are viewed by the same people tend to be placed together. In other words, if Program A and Program B are close together, this implies that a viewer who watches Program A is also likely to watch Program B. Consequently, closeness in this preference space may indicate that two programs are competing (if they are offered at the same time by different networks), complementary (if they are offered by the same network at different time periods), or unrelated (if located far apart in the preference space).

The second stage of our approach uses a recentlydeveloped technique called clusterwise logit analysis to obtain viewing segments. While all viewers are different, characterizing the viewing audience as being comprised of a small number of segments facilitates understanding of the viewing audience and thus provides a useful approximation of the true nature of the viewing audience. This stage enables us to describe each segment in terms of its program preferences, tendency to watch cable and non-network programming, and other characteristics.

The third stage models the on-off decision—the factors which make it more or less likely that a viewer from a particular segment will turn the television on or off. We use a standard logit model to model this stage.

While the main focus of this work was the development and illustration of a new approach for the analysis of television viewership, our empirical application on 1988 viewing data did reveal some interesting substantive findings. First, we found three distinct viewing segments, and reliability tests showed these segments to be quite stable.

One segment, the "Easterners," tends to be older, from smaller households, and cable subscriber. Another segment, the "Southerners," tends to be rural, less wealthy, less educated, and more prone to watch action shows. The most distinct segment in terms of viewing behavior, the "Westerners," tends to be younger, urban, wealthy, well-educated, and watches less TV on weekends. This is the only segment which shows any evidence of program content affecting whether or not to watch TV.

Another surprising result from our analysis was that preferences by each of the three segments were

<sup>\*\*</sup>x 10<sup>-2</sup>.



Figure 6

best represented by anti-ideal points, which provide a better understanding of what is avoided, rather than what appeals to these viewers. This finding suggests that viewers may in fact choose the "least objectionable alternative," as has been snidely asserted by some network executives.

Also, viewing segments varied considerably with respect to their tendency to prefer non-network programming (including cable) and their level of inertia. For example, "Easterners" are more likely to tune-in to a non-network channel, and more likely to stay tuned to the same channel at the end of a program.

The results from the on/off portion of our integrated model also lead to some interesting substantive conclusions. Not surprisingly, viewership by all three segments is highly affected by the particular primetime period, decaying as it gets later in the night. Most importantly, viewership at any given primetime period is highly affected by whether the TV was

on or off in the previous period, and to a much less extent, on whether the viewer was watching a show to be continued in the current period. Also, with the exception of the "Westerners" segment, the particular shows being offered at any time did not have any significant impact on the viewers' decision to watch or not watch TV! These viewers seem more likely to watch television than particular programs.

These substantive findings, based on a limited sampling period, are suggestive of the sort of results which can be obtained from this modelling approach. We would expect that the nature of the viewing audience and its preferences change over time, and thus that repeated application of these methods would provide a dynamic picture of how the viewing audience is changing over time. We hope that these models will be helpful as prototypes for future models which networks and advertisers can use to model viewing choice.

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