GEODEMOGRAPHIC SEGMENTATION: NEW METHODS, NEW RESULTS

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Background

Geodemographic segmentation or clustering in the marketing context involves classifying small geographic areas – for example, block groups, census tracts, or neighborhoods – into relatively homogeneous market segments. The exercise produces an "a priori" set of segments that are presumed to correlate well with individual preferences and consumer behaviors, though direct measures of those preferences and behaviors are not used explicitly in the classification process. While the goal of geodemographic clustering is to classify "places" – communities and neighborhoods – not the people who inhabit those places, and despite the obvious issues of ecological fallacy, clustering has generally proved a useful tool in the marketing context.

First generation (c. 1975-1985) cluster systems created by demographic data firms invariably spoke of "birds of a feather flocking together," that people with similar characteristics, preferences, and consumer behaviors tend to live in like neighborhoods. However, the times – and American society over the past 25 years – have changed. The extent of diversity – whether socio-economic, ethnic, cultural, lifestyle, life-stage, or other dimension – both within and across America's neighborhoods is such that a "useful" geodemographic cluster system must necessarily take into account unprecedented levels of "within neighborhood" differences as well as increased diversity

overall. This paper presents a methodological strategy for clustering in the marketing context that attempts to take that increasing diversity into account.

Fortunately, while diversity progressed, new tools and techniques have evolved to the benefit of geodemography. Advances in spatial analysis, geo-statistical software, and modeling techniques – along with the raw ability of computers to implement new clustering strategies – open the doors to spatial analytic worlds undreamed of only a few years ago. Geography – the science of location, spatial systems and networks, proximity, settlement context, and combinations thereof – is at the heart of geo-demographic clustering. This paper describes the results of a team effort of demographers and geographers at MapInfo Corporation* to produce PSYTE US Advantage, a segmentation product used for consumer market analysis.

Literature Review

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Within the general literature of statistical clustering techniques in a market research and geographic context, reviewed well beginning perhaps with Punj and Stewart (1983) and extending at a minimum to Openshaw and Turton (1996), clustering has challenged researchers in numerous ways. More recently, cluster techniques in the sciences of genetics, artificial intelligence and digital signal processing have made long strides in the ability of analysts to classify complex data into their principal structures.

One set of challenges revolves around two approaches to clustering, hierarchical and non-hierarchical. The former operates in two modes: agglomeration and disaggregation. Agglomeration basically takes N observations and iteratively arrives at a

^{*} The authors would like to thank and acknowledge the contributions of the other members of the PSYTE US Advantage development team: Anthony C. Lea, Danny Heuman, Chris Michels, and Fraser Baldwin. Peter Dixon provided invaluable support and vision with regard to the software infrastructure.

single, final cluster by combining pairs of previous clusters. Dissaggregation, on the other hand, starts with one cluster and iteratively divides clusters until N observations remain. Hierarchical approaches are generally computationally intense and restricted it use with small data sets. Moreover, this pairwise approach also results in less variance being captured when compared with the more holistic non-hierarchical techniques. In contrast, non-hierarchical approaches work better with large datasets and generally capture more of the variance in a dataset (Lea, 2003), a characteristic that suggests they are well suited to geodemographic clustering.

First generation classification techniques applied to census data relied heavily on non-hierarchical approaches, with the *K-means* type classifications being the most widely used. Basically, this approach would start with N random starting positions in M dimensional space. The process would iterate until all observations in the data space were optimally assigned to one of the N starting positions, which in turn were allowed to move in order to achieve optimality. There are two significant drawbacks to this technique: a) the random starting positions can have a dramatic affect on the final outcome, especially with a small number of clusters, and b) the measures of similarity between the starting positions (the centroids) and the observations are not necessarily sensitive to the variance within the data space. (Lea, 2003)

A "Second Generation" set of tools emerged in the 1990's when research in Artificial Intelligence and Neural Networks relating to pattern recognition and classification gained prominence (Schürmann, 1996). Some applications of these methods involved "machine vision" such as that used in the context of scanning vehicles at border crossings (Shenk, 2003). While the datasets involved were not necessarily large,

these new algorithms proved to be quite adept at separating the data objects from the "noise." Moreover, for pattern recognition analysts, especially those in a security context, "time was of the essence," as most requirements demanded real-time results. Fortunately, since geodemography rarely has a real-time demand, the application of Neural Networks could be applied with longer processing times in exchange for the ability to analyze larger datasets. This opportunity, applied to the present case, offered the distinct advantage of faster processing and, ultimately, greater discrimination among clusters.

Unfortunately, the Neural Network approach presents its own set of methodological challenges. Essentially, a neural network classifier shares many characteristics of K-means: it has random starting locations, it is iterative, and it uses a centroid-like classification scheme. However, its distinguishing benefit relative to Kmeans is how similarity measures are calculated. Unlike K-means that uses a single measure of similarity (a squared-error function; see Han 2001), in the case of a Kohonen Neural Net classifier, a multidimensional comparison is made that has greater discriminating power. Furthermore, to appreciate the differences with respect to processing times, when comparing the K-means and Kohonen classifiers, during an initial phase of this project, we found that several months of work with the former could be reduced to just a few weeks with the latter.

 Still, issues remain as to how to best utilize this technology in geodemography. Two issues, in particular, make non-hierarchical classifiers less than optimal. In the first place, they still rely on the user providing an initial desired number of clusters. Secondly, random starting positions are still used. While these conditions are not show stopping,

they remain detractors from the ultimate goal of developing a fully objective and successful process using non-hierarchical classifiers alone.

Hierarchical techniques, on the other hand, which have been applied less frequently due to their computational overhead, do not suffer from random start locations and subjective target cluster numbers. This discussion perhaps begs the question as to why, if computers are so much faster now, why can't hierarchical classifiers be used "brute force" to come up with clusters. Two reasons have been suggested (Lea, 2003) that would give pause in this regard. The first is that the hierarchical classifiers generally do not capture variance as well as non-hierarchical techniques. The second is that it remains difficult to control the final relative size of the clusters.

One emerging line of inquiry that seeks to use a combination of non-hierarchical and hierarchical techniques is the relatively new field in clustering called *auto-clustering* (reference?). Then, lying somewhere between the classic non-hierarchical techniques and auto-clustering of today are a set of methods known as two-stage clustering (Parthasarathy 2003) and hierarchical self-organizing maps or SOMs (Hagenbuchner, et al. 2003). These approaches attempt to combine the best features of hierarchical clustering with those of non-hierarchical clustering.

The research presented here represents an attempt to utilize the best available knowledge with regard to geo-statistical clustering techniques in a "consumer demographics" context. Because geodemographic clustering generally occurs in a competitive, market-oriented environment, additional constraints (e.g. positioning) are placed on the development process. Nevertheless, a central purpose of the present paper

is to suggest additional linkages in the ongoing discussions among demographers and geographers on both the applied and theoretical fronts.

The Development Process: Rationale and Summary

To some, geodemographic clustering in the marketing context necessarily involves a subjective process in which the selection of initial variables, the manner of their operationalization, and their purpose-driven weighting heavily influence the final clusters. However, today's computing environment, coupled with new methods of spatial analysis, obviate subjective methods to a greater degree. The authors suggest that subjectivity in clustering – including the implementation of predetermined cluster characteristics – is not necessary, indeed, is inhibiting to an optimal cluster solution. One primary tenet in the current research, therefore, is to "let the data speak for itself," and thereby create a more scientifically reliable set of clusters.

In summary, the research team adopted a two-stage clustering process. The first stage involved using a proprietary Kohonen classifier while the second stage used a hierarchical classifier. The objective of the first stage was to develop a set of clusters that captured the essential demographic characteristics of neighborhoods along with their settlement context (defined below). This was accomplished with the Kohonen classifier creating sub-clusters or "atoms." The atoms (numbering in the hundreds) delineated a neighborhood sub-cluster set that would in turn be the starting point for the second stage of the process. A larger topic, not discussed in this paper, is that the "second stage" process can in fact move in several directions. The software infrastructure developed for

this project embodies the vision of permitting "custom clustering solutions" involving the introduction of additional proprietary datasets.

The two-stage process described here relies on a several of fundamental assumptions. First, the census-defined Block Group is the basic geographic building block for the system. Second, demographic and settlement context measures are the only core data used in the first stage. Third, additional datasets including, for example, measures of consumer "lifestyles," can be introduced for the second-stage processing but would not change the fundamental definitions of the neighborhood typology or the initial sub-cluster set. That is, the "atoms" and the initial neighborhood set are sacrosanct.

The first assumption ensures that reliable and valid data are always used, regardless of the application. Considering that a geodemographic clustering system is an a priori system, statistical reliability is paramount. To that end, census Block Group data are used as the primary unit of observation. In all cases, Block Groups are the starting point and all non-Census data used must be statistically significant for each Block Group represented. $(N = 208,270)$

The second assumption reinforces the fact that neighborhoods, census tracts, and block groups are best described in demographic terms. This may seem obvious. However, clustering deals fundamentally with a demographic environment and data related to the demography of the population best describe that environment. It appears untenable to maintain that significant amounts of non-demographic data – consumer purchase behavior, lifestyle indicators, and other non-census-based measures – however well operationalized, can substitute for the basic demographic characteristics of a population for clustering purposes. Moreover, descriptors pertaining to settlement context –

population density, proximity to commerce, complexity of street networks, and other measures – complement demographic attributes by providing spatial context to the analysis, thus adding geographic dimensionality and discrimination for the clustering algorithms.

The third assumption stipulates that the operational groupings of the block groups resulting from the first-stage process are, in fact, neighborhood sets. That is, the atoms fairly describe "neighborhoods" because they have similar geodemography. Once these sets are defined, they are never altered, and they become the multidimensional, operationalized definition of the neighborhood population. They may be further aggregated in subsequent stages depending on various application objectives, but they would never be disaggregated.

One advantage of the approach to clustering described here is the need to create atoms occurs only once per census period. Since atoms are immutable there is no need to recreate them for each clustering application. Given that the majority of work in a clustering solution is the collection, preparation and segmentation of atom level data, additional clustering solutions, or "updates" to such solutions, can be achieved with much less repetition of effort. With the basic methodology reviewed, we can now describe how these methods were applied in the development of PSYTE US Advantage.

Setting Up the Data

The development of PSYTE US began with processing and defining Census 2000-based databases. Next, the specific census variables that would go into the process, at their corresponding spatial scales (e.g. block group and census tract), were selected and

defined. In a clustering process, the character of the input data determines to a large extent the types of clusters that emerge in the output. For example, if family structure variables are not input, the output clusters will not have a family structure dimension. Likewise, if too many family structure variables are included relative to other variables, then the segmentation system will be predominately family structure clusters.

Several important statistical issues were keep in mind as the input variables were selected. In the first place, if the clustering technique is a parametric method (e.g. Kmeans), then all variables should be ratio data. However, if a non-parametric process is used (e.g. Neural Networks) then nominal, ordinal and interval data could be included.

The second statistical issue is whether the candidate variables are statistically reliable, especially that they are derived from a sufficient sample base in the case of SF3 variables, and that the inherent variability is sufficient to provide statistical discrimination in the cluster solution. Results will be less valid if all variables are not significant for each geographic unit being clustered. In general, the U.S. Decennial Census is an excellent source of reliable data since the data are collected at 100% and 20% samples. The same cannot be said for household list data, for example, that is sourced from commercial surveys, subscription lists and product registrations.

Third, every variable selected must also have a corresponding denominator or weighting variable. This requirement allows the data to be normalized with respect to its geographic level and provides for an accurate calculation of weighted means and standard deviations. Since all geographic units are not the same size in terms of area or population, the analyst must account for this by either calculating averages (e.g. income) or percentages (e.g. cohort composition). Not doing so would bias the classification

toward grouping geographies together based on their size rather than their true demographic profile.

Finally, considerable thought was applied to how the variables are weighted. For example, K-means clustering can use an explicit weighting scheme whereas neural net techniques generally use an implicit weighting scheme. One advantage of neural net techniques as used in PSYTE US is they can handle more variables of similar character. Therefore, as described below, several variables were selected to represent each key demographic dimension in the system.

Cluster Dimensions

Since geodemographic clusters are generally used in marketing and site analytic contexts, several sets of socio-economic and cultural variables were selected as primary inputs. Other variable types such as settlement context, population density, proximity to certain retail environments and community services, as well as lifestyle and purchase behavior variables (for the second stage analysis), were also developed and included in the processing. In the end, both census and non-census type variables were used. The non-census variables were normalized to the geography through the calculation of geographic potentials. The primary census-demographic variable sets included: age, dwelling type, education, employment, race and ethnicity, family structure, group quarters, Hispanic origin, home language, household composition, immigration, income, industrial classification, geographic mobility, mode of travel to work, occupation, and place of work.

The following comments illustrate some of the content and measurement issues considered in the development of PSYTE US for each of these variable sets:

Income

Four types of income statistics were included: 1) mean and median family and household income, 2) income distributions of family and household, 3) sources of income as expressed as a percentage of total income, and 4) income distributions by householder age.

Education

This category serves two objectives: identify the educational attainment of persons (which can correlate with affluence) and discern the current enrollment levels of the population to distinguish college towns from other types of residential areas.

Group Quarters

Due to the generally concentrated populations of military personnel, college students and correctional facility inmates, it is important to identify these areas and essentially "set them aside" during the clustering process since their consumption behavior is quite distinct. Using census data on populations in military barracks, college dorms, and prisons best identifies these areas. Incidentally, MapInfo data developers have corrected some, but not all, of the most egregious group quarters location errors in Census 2000.

Dwelling Type

Many characteristics are captured by dwelling characteristic or housing unit data. The principal ones are: size of dwelling (e.g. number of rooms or units), owner or renter occupancy, vacancy rate, housing vintage, and home value. Such data enhances any profile of residential areas with characteristics like level of affluence, areas of single-family detached housing, concentration of apartments, new or old communities, and seasonality of occupation.

Geographic Mobility

Geographic mobility includes a range of concepts including place of birth data, internal migration, length of residence, year of arrival, and immigration status. For example, identifying the classic Burgess 'Recharge Zones' helps determine neighborhood evolution or stability. Also, high levels of geographic mobility in some urban areas can be an indicator of gentrification.

Place of Work and Commuting

Place of work data determines the extent of commuting on a county and urban or metropolitan level. This helps to characterize commuting flows, commuting times, methods of transportation, and patterns such as inter-urban, intra-urban or extra-urban transit.

Mode of Travel

Not only is the mode of travel interesting in itself, but this concept also provides important insights into settlement context. For example, walking to work may

indicate mixed zoning (residential and business) or level of urbanity when combined with the presence of rapid transit systems.

Employment

Three general statistics are covered by this category: percentage of persons employed or in the work force, the number of hours worked per week, and the number of weeks worked per year. Thus, not only does such data indicate the general employment level in an area, but the data are also excellent for profiling full-time, part-time and seasonal employment.

Industrial Classification

Provides insight into the "industry" or area of work in which persons are employed. It is one key discriminator for affluence, but also describes the economic structure of area and the work interests of the population.

Occupation

Combined with industry, occupation indicates the range of skills and general compensation levels for the working population. Due to the number of groups within this category, major occupational groups were used and occupations were also summarized into three categories: Blue Collar, Gray Collar, and White Collar.

Age

The variables in this group provide the essential cohort population distribution and permits insight into the age profiles of a neighborhood. Family structure differences and the presence of bimodal age groups, for example, are important indicators of the nature of a community.

Race, Hispanic Origin, and Ethnicity

Providing indicators of cultural diversity, which potentially contribute to differential consumption behavior, these data measure levels of diversity, indicate specific trends in diversity (e.g. suburbanization of minority populations), and offer descriptors of the "ethnic character" of a cluster.

Immigration and Ancestry

These variables provide key pieces of information about the immigrant population and their surrounding community. Period of immigration provides insight into the "age" of ethnic neighborhoods and whether they are still being "recharged." Ancestry and country of birth provide additional cultural information.

Home Language

While home language can be seen to duplicate the statistical discrimination of neighborhoods offered by Hispanic, Ethnicity and Immigration variables, it provides an important additional descriptor: cultural assimilation, both in terms of knowledge of official languages, and retention of traditional languages at home.

Household Structure and Family Status

Capturing data about the number of families, family structure, marital status and presence of children provides a set of powerful indicators that relate to consumption behavior as well as to the overall household composition in the neighborhood.

The Clustering Process

Once the database is set up and normalized, the actual clustering process can begin. MapInfo analysts used the two-stage methodology as described above. The first stage involved the application of neural network geo-statistical techniques to classify the 209,780 block groups with 400+ census variables. The original PSYTE US developed by MapInfo analysts with 1990 Census data involved testing and experimentation with several neural network routines. The new PSYTE US implemented a proprietary neural network routine developed over several years of further testing and research. In general, neural network techniques, which involve pattern recognition in ways that mimic the human brain, have outstanding capabilities for identifying patterns in socio-economic data.

A perennial issue with geodemographic clustering is the problem of outliers. While great clusters may be produced, concerns remain about observations that are significantly different from the mean of the cluster across several dimensions. The issue is: Which is the best (most appropriate) cluster assignment of the outlier block group? The use of "atoms" in the first stage of the clustering process minimized the occurrence of outliers in PSYTE US. Several hundred atoms – smaller, preliminary clusters of block groups – were created. Since there were hundreds of atoms, the statistical likelihood of outliers existing at the atom level was greatly reduced. The second stage of the clustering process was executed on these smaller, statistically similar building blocks.

A Note On Homogeneity

In an idyllic world a clustering routine produces highly homogenous clusters. Clearly, the real world is different and ultimately more interesting. As discussed above, PSYTE US is a clustering system for neighborhoods, not individuals or households. Neighborhoods, like the people who inhabit them, are inherently heterogeneous. The issue is how to measure neighborhood heterogeneity. Neural network techniques are, in fact, uniquely able to measure not only the degree of homogeneity but also the specific combinations of socio-cultural dimensions that characterize a particular cluster's "heterogeneity." For example, many rural neighborhoods have been transformed by the presence of urbanoriented workers and their families. Likewise, some Hispanic neighborhoods are influenced by interactions with African American families, while others are influenced by the presence of recent Asian immigrants. Moreover, since social processes are not generally random, there is a significant likelihood that heterogeneous neighborhoods in one region will have characteristics of heterogeneity similar to neighborhoods in other regions. The authors confirmed that geodemographic clustering is still applicable to the task of grouping neighborhoods by their similar characteristics despite their increasing diversity over time.

Hierarchical Clustering

After the "atoms" were created, based primarily on socio-economic and demographic variables along with selected measures of settlement context, the next stage used hierarchical clustering techniques to group the 400+ atoms into the final 72 clusters. In this second stage of clustering, consumption data (e.g. car purchases, retail infrastructure

capacity, lifestyle indicators, etc.) were combined with the geodemographic atoms and further clustered. The proprietary hierarchical technique used provided more precise control over the clustering process (for reasons discussed above) and allowed researchers to "craft" the clusters in a scientifically reliable way.

In addition to hierarchical clustering techniques, Principal Components Analysis (PCA), a special implementation of Factor Analysis, was used. PCA is valuable as a method for its ability to reduce large datasets into their "principal components." Each principal component represents a specific dimension of variance within the database and discards noise, or ineffectual data. Thus, as the hierarchical process was used to agglomerate atoms into final clusters, and as the analysts did not want too many variables to bias the process along certain dimensions, PCA was used to provide meaningful components among intentional characteristics without the need for a large number of variables.

Final Steps

 Once the final 72 neighborhood clusters were established, and the analysts were content with their statistical reliability, the process of "visioning" could begin. Visioning in the process of describing the clusters consistent with their underlying characteristics. Cluster descriptions must ring true for the general characteristics of each neighborhood but also for their unique identifiers. Often, a unique combination of characteristics informs the "vision" of a cluster. Ultimately, each cluster is distinguished from all other clusters in the system, while simultaneously sharing characteristics similar to other clusters. Readers are referred to the PSYTE US cluster descriptions – maps, statistical

descriptions, and highlights – to more fully appreciate the final clusters. (See PSYTE US Web Site.)

Conclusion

PSYTE US is fundamentally a geodemographic cluster system. Geodemographic cluster systems, in contrast to household-based systems or hybrid systems, use a census block group neighborhood base to provide stable and statistically reliable cluster assignments. Much like "settlement context" establishes the urban-suburban-rural nature (in a word: "urbanity") of a place, the "neighborhood context" provided by PSYTE US provides a unique and identifiable description that permits marketers and site location specialists to use the system effectively. PSYTE US thus provides a multidimensional framework that allows analysts to capture the complexity of American consumer culture without having to manipulate literally thousands of census variables.

Over the last half-century long strides have been made regarding the methodologies and technologies used to segment geodemographic data sets. One of the principal goals during this evolution has been the increased rigor with respect to the statistical models and the scientific method thus migrating subjective human understandings to more reliable computational models. Simultaneously, the debate and interplay between hierarchical and non-hierarchical techniques has generated applications and processes that should lead to further advances. One promising advance, alluded to in the literature review, is the area of "auto-clustering." Auto-clustering approaches promise to remove all subjective input to the process and analyze data based strictly on their structure of variance (Rauber et al. 2002). While clearly in early development, they hold some

promise and could eventually relieve the researcher of all tedious decisions except for the most important of all: What data are important in an a-priori segmentation system?

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Appendix

