Improving Marketing Efficiency in the Retail Bicycle Industry through Geospatial Segmentation

Mitchell C. Beckner, Ross A. Jackson, and Kevin S. Steidel

***Abstract*— Developments in technology and communications have placed more emphasis on the demand side of consumer markets due to the fact that potential customers now have the ability to conduct in-depth research and purchase products from a larger number of sources. Market segmentation is a technique that has been commonly used to improve the understanding of customer values and to maximize business resources. However, traditional methods are often heavily dependent on large amounts of historical data which many small to medium businesses do not have. This project's objective was the creation of a geospatial customer segmentation model that could be used to increase the effectiveness of marketing and advertising funds in the retail bicycle industry without reliance on historical customer purchase data. U.S. Census data at the census block level was used with K-means clustering to produce primary segments that were then further divided into subclusters in a divisive, hierarchical manner. These segments were evaluated in order to determine the characteristics and decisive buying criteria of each group. Individual businesses can then prioritize these segments and develop specific marketing strategies based on the segment characteristics and the particular business objectives. If customer data is available or collected going forward, that data can be merged with the segmentation model using the Census Bureau's geocoding API.**

***Index Terms*—Cluster analysis, data mining, geospatial, market segmentation.**

I. Introduction

Rapid developments in information and communication technology have changed the role of the customer in modern marketplaces. Businesses must now pay more attention to the demand side of the business equation since potential customers have the ability to research and purchase from a much wider selection of alternatives. Market segmentation is a technique that is often used to help put customers first and maximize resources. However, while the benefits can be great, implementation can be difficult and many small to medium businesses do not have the detailed data on their customers or their historical transactions that can be required [1].

The primary objective of this project is to demonstrate that the use of a geospatial customer segmentation model can increase the effectiveness of marketing and advertising funds in the retail bicycle industry. The segmentation model uses an unsupervised clustering algorithm to divide the potential customer dataset into smaller groups based on similarities without requiring historical sales data. These segments can then be used when planning and executing marketing campaigns to more efficiently reach customer groups. The model created in this project was then presented to potential end users and a survey offered. Survey results were analyzed in order to determine the validity of the project's hypothesis.

Traditionally, customer segmentation has been a common method used in marketing studies and much work has been performed in this area. Table I summarizes a cross section of the many studies performed. These studies cover a variety of business areas as well as several different methodological approaches. However, most if not all of these methods attempt to attach a predicted or potential value to customer segments using existing historical customer sales data, or survey data designed to reveal customer attitudes. Recency, Frequency, and Monetary (RFM), of Customer Lifetime Value (CLTV) are often used as target values when creating these segmentation models.

While this is certainly a valid approach that can provide quality results, the authors of these studies often note that large amounts of data are required [2] and that implementation of the methods can be complex and burdensome. In addition, methods relying on existing customer data generally are not useful to businesses for the purpose of acquiring new customers [3].

Although many studies have been performed on the retail sector in general, the author of this study was unable to locate any prior market segmentation studies on the retail bicycle industry. Many studies related to cycling focus on commuting and the shift from automotive to bicycle transportation. Li, et al. [4] used household survey data to determine traveler attitudes. Structural equation modeling (SEM) and K-means clustering were then used to create segments for which strategies were created to promote bicycle commuting. Outwater [5] also used SEM to identify traveler attitudes and predict mode of travel choices. The theory of planned behavior as used by Anable [6] to cluster individuals into groups based on their potential for switching between modes of travel. Finally, Ryley [7] used Scottish household survey data and cluster analysis based primarily on life stage. While this study did recognize that its participants favored leisure cycling trips, the study's focus was again on targeting strategies for reducing automobile usage.

A market segmentation study such as this, applied to the retail bicycle industry, while niche, is generally of relevance to those interested in research pertaining to international trade and economic analysis. First, broadly speaking bicycles are utilized globally. Bicycle interest around the world, according to Oke, Bhalla, Love and Siddiqui, "is growing within the public health, transportation and geography communities" [8].

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So as far as the object of inquiry the topic has significant international relevance. Second, in terms of the primary analytic technique utilized, market segmentation has been used within an international context to examine the cell phone market [9-10], travel [11-12], environmental focus [13-14], and grocery stores [15-16] to name just a few application areas. In the application of analysis in R, one can critique both the notion of free software [17] and the philosophical foundations of verification and validation of one's analytic models [18].

As noted above, while these studies provide valuable insight into portions of the bicycle market, they are heavily dependent on the collection of data specific to the study and they do not address areas of the retail bicycle market including recreational riding, fitness riding, and racing. The focus of the current study is to develop a geospatial segmentation model based on widely available data that could be used both to identify potential new customers and to better understand the values of existing customers. The model would not require historical customer data but could incorporate and increase the value of such data if it were available.

TABLE I: MARKET SEGMENTATION STUDIES

Author(s)	Application	Method
Chan (2007)	Automobile Retailer	RFM/LTV Modeling
Yoseph, Malim, Heikkila, Brezulianu, Geman, and Rostam (2020)	Department Store Sales	EM (Expectation Maximization) / CLTV
Kim, Jung, Suh, and Hwang (2005)	Wireless Telecommunivcations	LTV Modeling
Ryley (2006)	Bicycle Commuting	Life Stage Clustering
Anable (2004)	Travel Behavior	Attitudinal Theory / Clustering
Outwater, Ben-Akiva, and Kuppam (2003)	Ferry Commuting	Attitudinal Theory / Structural Equation Modeling (SEM)
Jonker, Piersma, and Van den Poel (2004)	Direct Mail Marketing	RFM/ Markov Decision Processes
Li, Wang, Yang, and Ragland (2013)	Bicycle Commuting	Attitudinal Theory / Clustering

II. MATERIALS AND METHODS

The approach taken by this study in modeling segments for the retail bicycle market is presented below. The data set is described along with the importation and transformation methods employed. This is followed by a discussion of the clustering method used.

A. Data

The primary source of data for this project was the United States Census Bureau [19]. Data was imported into R at the census block, or Zip + 4 level using the Census Bureau's API. A census block is the smallest level of geography that basic demographic data is available for and generally contains between 600 and 3,000 people. As shown in Table II, ten tables from the 2010 decennial census were combined with seven tables of 5-year census data from 2011 through 2019. The data collected covered the fifty US states plus the District of Columbia.

Data cleaning was performed with erroneous values removed along with data from census blocks with zero population. Data from 5-year tables was not available at the census block level of granularity and therefore had to be expanded to block level using the HUD Crosswalk file [20]. Using this file, proportional percentages between census tracts and blocks comprising them were created. These were calculated based on both population and the number of households. These percentages were then used to evenly distribute the totals from tract level aggregations across the smaller blocks within each tract. Data from the individual census tables was then joined using each census block's GEO ID, the numeric code that uniquely identifies all geographic areas for which the Census Bureau tabulates data [19]. Due to the size of the resulting files, as well as the system resources required for processing those files, data was organized into five regions [21]. This eased the computational demands of the imputation process that followed.

Missing data values were imputed in R using the mice package's predictive mean matching method [22]. The imputed values were then examined to ensure that mean and median population values remained reasonably unchanged and that no unrealistic or outlier values were created. Following imputation, the five regional files were combined. The resulting dataset used for the segmentation process consisted of 125 variables from each of 6,207,027 unique census blocks.

TABLE II: CENSUS TABLES USED

Decennial Census Tables

Table #	Subject	Year
P2	Urban and Rural Population	2010
P3	Race	2010
P4	Hispanic or Latino Origin	2010
P12	Sex by Age	2010
P18	Household Type	2010
P28	Household size	2010
P37	Average Family size by Age	2010
H1	Total Households	2010
H2	Urban and Rural Housing Units	2010
H4	Housing Tenure	2010

5 Year Census Tables

Table #	Subject	Year
B08136	Aggregate travel time to work by mode	2011-2019
B08201	Vehicles available	2019
B08301	Means of transportation to work	2019
B15002	Sex by educational attainment	2019
B19013	Median Household income	2019
B23025	Employment status	2019
B28010	Computers in Household	2019
B28011	Internet subscriptions in household	2019

B. Clustering

K-means clustering was selected as the method for creating segments. This algorithm is commonly used to solve clustering problems and has been shown to be effective when dealing with complex, high dimensional data [23]. K-means clustering is a non-hierarchical process that begins by selecting a pre-determined number (k) of observations as the initial cluster centroids. Each observation is then assigned to the cluster that has the closest centroid, based on Euclidean distance in this case. When all observations have been assigned, the position of the centroids is recalculated and observations are reassigned. This process is repeated until the cluster centroids no longer change [24].

Prior to performing the clustering, a reduced set of 46 variables was selected. These variables included data from each census table however, some of the data was binned differently, and when variables appeared to be collinear, only one was included. This data was then normalized to a scale of 0 to 1 using the formula below for each variable:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{1}$$

This min-max scaling places all variables on the same scale and eliminates the possibility of any individual variables dominating the selection of clusters [25].

The first step in K-means clustering is to specify the desired number of clusters in the final model. The objective here is to define clusters such that the variation within each group is minimized:

$$minimize\left(\sum_{k=1}^{k} W(C_k)\right) \tag{2}$$

Where C_k is the kth cluster and $W(C_k)$ is the within cluster variation. The Elbow method for determining this optimum number of clusters requires that the clustering algorithm be run multiple times for varying k values. The within cluster variation is then plotted against the number of clusters. The location of the bend or elbow in the resulting plot is generally considered to indicate the optimal number of clusters [26]. Fig. 1 shows the elbow plot for the data in question. Based on this, it was decided to compare the segments resulting from k values of 7, 10, and 12. The final selection of 10 primary clusters was based on a compromise between minimizing within cluster variation and creating a reasonable number of easily understandable segments. Analysis of these primary segments is given in Section IV below.

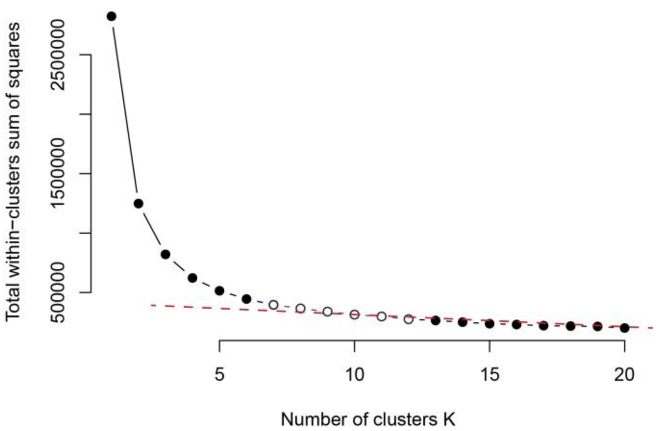

Fig. 1. Elbow plot of normalized clustering results.

In order to provide potential for more granular segmentation, should it be desired, the ten primary segments were then further divided. This was done in a divisive, hierarchical manner, breaking each primary cluster into two parts. This process was performed a total of three times resulting in a total of eight sub-groups for each primary segment at the most granular level (see Fig. 2). It should be noted that due to the size of the dataset, hierarchical clustering algorithms were not successful. Instead, the sub-groups were created using iterations of K-means clustering.

III. Results

In order to turn the clustering model into segments that could be useful for marketing purposes, further analysis was required. Following a modified version of the procedure described by McDonald and Dunbar [27], the next step in the process was a close examination of the retail bicycle market itself. The US bicycle industry generally amounts to approximately $6 billion each year. This revenue is spread across five primary distribution channels; mass merchants, specialty retailers, full-line sporting goods stores, outdoor specialty stores, and other retailers including internet sales. Mass merchants are made up of department, discount and toy stores and account for approximately 74% of unit sales, representing 23% of the total revenue. Specialty retailers (bike shops) account for 13% of the unit sales but almost 50% of the total revenue. These specialty retailers are the primary focus of this study. Sporting goods and outdoor retailers capture approximately 8% of the revenue each with the "other" category representing 3% of total revenue [28]. Additionally, there are several categories of bicycles that are intended to meet a variety of user needs. These categories include mountain, road, comfort, youth, cruiser, recumbent/tandem, electric, and folding travel bikes.

Each primary segment resulting from the clustering described above was examined in detail in order to determine its defining characteristics and the likely values of its primary decision makers. The categories of bicycles most likely to be used by a given segment were suggested along with the importance each segment would give to a set of key discriminating features (KDFs). These KDFs were then interpreted in terms of the benefits they would provide, or need they would fulfill for a given segment. These needs are referred to as the decisive buying criteria (DBCs) since they determine which competing offer a customer will choose [27]. During the process of examining segment traits and defining DBCs it was discovered that segments 1 and 7 were very similar. Therefore, these two primary segments were combined into one and new subclusters were created for the combined group. A brief description of each primary segment follows, and the importance of DBCs for each group are given in Table III below.

City Seniors – Predominantly white, 2 person families. They are well educated with a large percentage over the age of 60.

Country Comfort – Predominantly white, rural 2 person families with a high percentage age 40-59, and 60+.

Downtown Diverse – A racially and ethnically diverse segment with a high percentage age 20-39. This is an upper mid income group that is well educated.

Family Homesteads – This is a rural group with a high Hispanic percentage. They are second highest in those under age 19 and have the highest percentage of large families.

Metro Renters – Predominantly black, low income group with a large percentage of single female families. This group is highest in use of public transportation.

Midtown Movers – Racially diverse with a high percentage of Asians, and people aged 20-39. They are very well educated and the second highest income group.

Neighborhood Youth – Urban segment with a high Hispanic percentage. This group is highest in people under age 19 and lowest in those over 60.

Rustic Retreat – Rural 2 – 3 person families with lower mid-scale income and low access to technology.

Urban Affluent – High income, highly educated families of 2 to 4 people with a high percentage age 40-59. This group has the highest percentage of bike racers.

With the segments created and defined, shapefiles of the 2010 census blocks were obtained [29]. These maps and the final segmentation model dataset were then imported into the Tableau visual analytics platform. A dashboard was created (see Fig. 3) that allows the user to enter a desired zip code. The dashboard will then display a map of the selected code area with each census block color coded to its primary segment. The demographic characteristics of the zip code area are displayed including the names and numbers of each segment present. The user can drill down to more detailed descriptions by clicking on map or chart items.

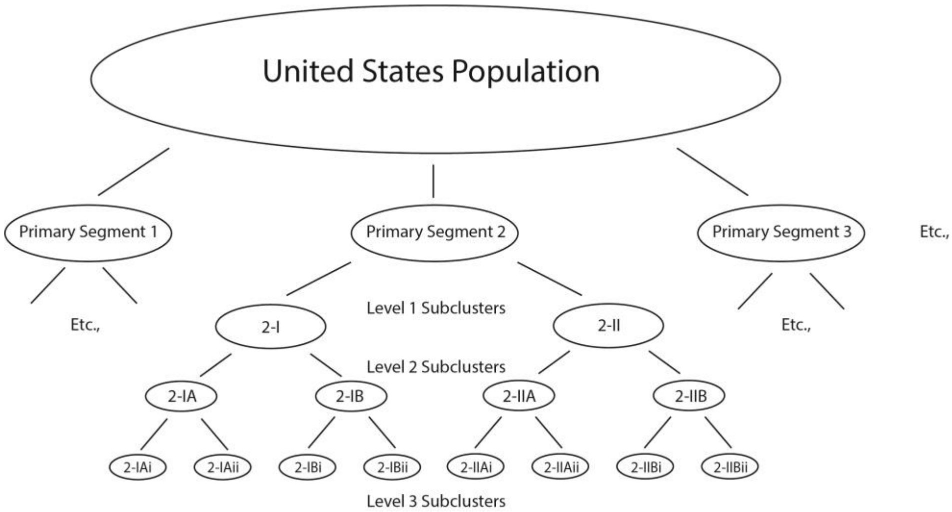

Fig. 2. Schematic of data clustering.

TABLE III: DECISIVE BUYING CRITERIA BY PRIMARY SEGMENT

DBCs Primary Segment	Eye Catching	High Performance	Reliable	Upgradable	Holds Value	Hands-on Purchasing	Shop from Home	Price
City Seniors	♦	♦♦	♦♦♦		♦♦♦	♦♦♦		♦♦
Country Comfort		♦♦	♦♦♦		♦♦♦	♦♦♦		♦♦
Downtown Diverse	♦♦♦	♦♦	♦♦		♦	♦		♦
Family Homesteads	♦		♦♦♦	♦			♦	♦♦
Metro Renters			♦				♦♦	♦♦♦
Midtown Movers	♦♦♦	♦♦♦	♦♦	♦♦	♦♦	♦♦		♦
Neighborhood Youth	♦		♦	♦		♦		♦♦♦
Rustic Retreat			♦				♦♦	♦♦♦
Urban Affluent	♦♦♦	♦♦♦	♦♦	♦♦	♦♦	♦♦		♦

IV. DISCUSSION

In order to effectively use the results of this geospatial segmentation, a business will need to evaluate the attractiveness of each marketing segment and determine appropriate marketing strategies for those it wishes to cultivate. The company's resources should be focused on the segments that provide the greatest opportunities in terms of growth, profit, or other business objectives. The company's ability to compete for customers in a given area must also be considered when prioritizing market segments.

Once segments have been selected for targeting, the marketing strategy must be formed. In the current business environment, this will generally involve a multichannel approach where several routes to market are used in an integrated fashion. Often, different channels are used at different points in the transaction process and these channels can vary depending on the traits and values of the potential customer [27]. The choices that would be most appropriate to a given situation will naturally depend on the specific segment targeted and objectives of the company. However, the following hypothetical example demonstrates how the segmentation model can be applied.

A downtown bicycle retailer wishing to sell excess inventory of recumbent bicycles could examine the primary customer segments and determine that, due to their age and disposable income, the City Seniors and Country Comfort segments offered the highest proportion of individuals likely to be interested in making a purchase. The Urban Affluent and Rustic Retreat segments are also found to have a large number of potential customers. The shop places a prominent advertisement for the recumbents on its website along with ads through Google and Facebook for the specific zip code areas. However, the Country Comfort and Rustic Retreat segments have lower than average access to computers and mobile devices. To increase the likelihood of establishing an initial dialog with these potential customers, a postcard is designed advertising the product and is mailed to the specific zip + 4 areas containing the prospective buyers. The ability to focus efforts on small geographic areas means more effective use of advertising funds. These strategies can be further refined making different offers to different groups based on the segment's values. Offers and areas can be further refined by drilling down into the more specific data found in each segment's subclusters.

Another way that the model can be used is by the incorporation of existing or collected customer data. Using the Census Bureau's geocoding api, the Census block GEO ID for an individual can be obtained in just a few seconds by entering only the person's address. As noted above, this GEO ID is the unique identifier used by the model and therefore, using this information the individual can be associated with their specific market segment all the way down to the most granular subcluster. Beginning with only an address, data from each of the 125 model variables can be associated with the customer.

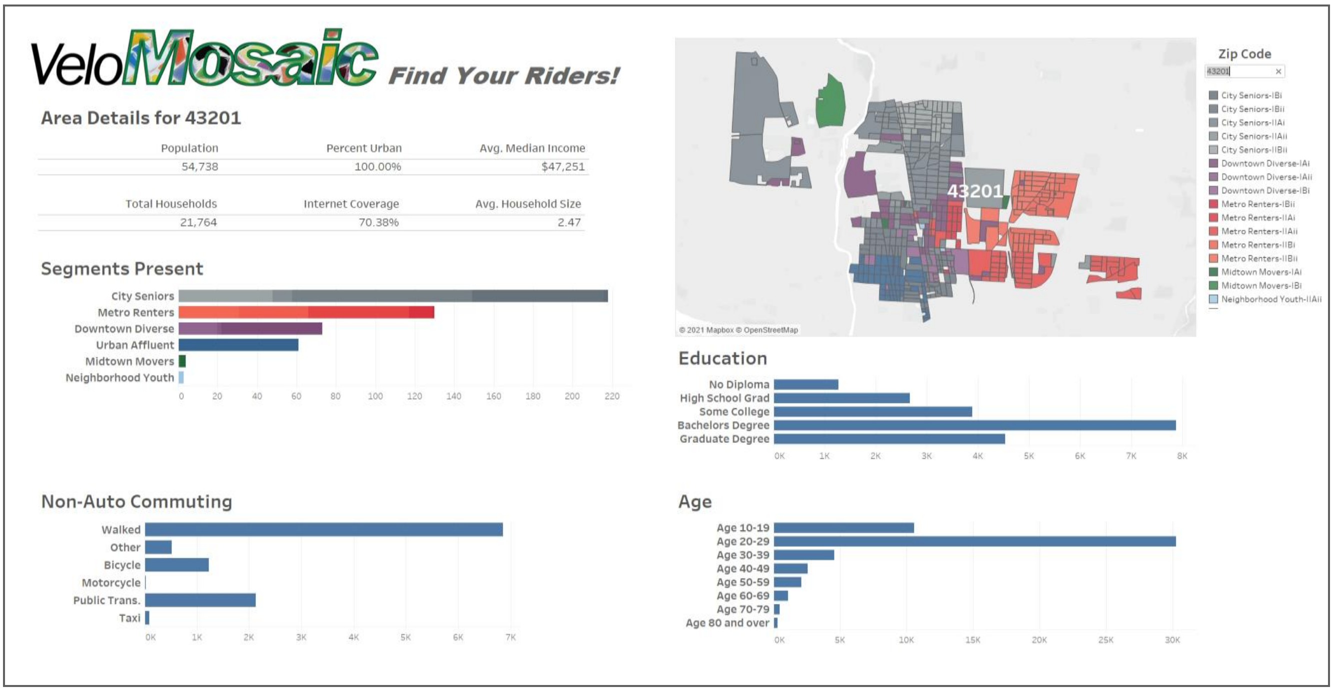

Fig. 3. Segmentation dashboard.

V. Conclusion

In order to evaluate the project hypothesis that the use of a geospatial customer segmentation model can increase the effectiveness of marketing and advertising funds in the retail bicycle industry, a video featuring a demonstration of the segmentation dashboard and explanation of its potential uses was created. This video was sent to 40 potential users and posted on various social media sites. Following the presentation, viewers were asked to complete a survey asking for their background as a retail bicycle and/or marketing professional, as well as their opinion on the potential effectiveness of the segmentation modeling project. Opinions of the effectiveness of the project were ranked as one of four levels: *Definitely Would be Effective*, *Probably Would be Effective*, *Probably Would Not be Effective*, *Definitely Would Not be Effective*. The survey responses were then compiled and analyzed in order to determine the validity of the project hypothesis. The null hypothesis was that survey responses would be evenly distributed across the four levels and therefore the "Effective" proportion would be equal to the "Not Effective" proportion. The alternative hypothesis was therefore that these proportions would be different from each other. The structure of the two tailed hypothesis test is given as:

$$H_0: p_1 + p_2 = p_3 + p_4$$

or

$$H_0: p_{effective} = p_{not\ effective}$$

$$H_a: p_{effective} \neq p_{not\ effective}$$

A goodness-of-fit chi-square test was used to evaluate the proportion of survey responses believing the project to be effective was 0.916 compared to 0.084 ineffective. The calculated X^2 (3, N = 24) = 17, p < .001 was statistically significant (α = 0.05), resulting in the rejection of the null hypothesis. We cannot state that the fit of equal proportions is sufficient and instead conclude that there is strong evidence that the use of a geospatial customer segmentation model as presented in this project, can increase the effectiveness of marketing and advertising funds in the retail bicycle industry.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

M. C. Beckner developed the idea for this study, collected and analyzed the data, researched, and wrote the initial draft of the paper, and edited the paper for publication. R. A. Jackson edited the paper for publication. K. S. Steidel supervised the research. All three authors approved the final version of the paper.

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