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A Visual Approach for Identifying Consumer Satisfaction Segments

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A VISUAL APPROACH FOR IDENTIFYING CONSUMER SATISFACTION SEGMENTS

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ABSTRACT

Much of today's consumer satisfaction research relies on ratings obtained through the administration of consumer surveys. A key item of interest to the researcher is the existence of underlying segments in the market place. Such information can be uncovered by studying the shape of the distribution of the obtained consumer satisfaction measure. The shape of this distribution can for example provide insights on the number and size of the underlying segments in the market place. This paper discusses various approaches available for graphing the distribution of consumer satisfaction responses and demonstrates the use and benefits of a proposed non-parametric method.

INTRODUCTION

Marketing managers often rely on ratings obtained through surveys to assess the degree of satisfaction experienced by consumers. The use of surveys in consumer satisfaction research has in fact witnessed a dramatic growth in the past two decades, and corporate use of customer satisfaction research has contributed billions of dollars to the market research industry (e.g., Advertising Age 1993; Gengler and Popkowski 1997). Survey-based studies of consumer satisfaction span the business horizon from small local retailers to large multi-nationals and cover industries ranging from insurance and financial services to the automotive and home appliance industries. Customer satisfaction measurement has therefore become a standard part of corporate performance assessment in many organizations (Parasuraman et al. 1991; Rapert and Babakus 1995).

Once a customer satisfaction survey has been administered, one typically relies on the emerging basic statistics such as the mean and the variance to make the necessary managerial judgements. For example, year-to-year comparisons can be conducted and comparisons to specific baselines and benchmarks can be made. However, in addition to the mean and the variance, managers can often rely on an equally vital measure: the distribution of the satisfaction ratings. The shape of the distribution of the satisfaction ratings provides one with a better understanding of the customer base. For example, the existence of a multi-modal distribution of satisfaction ratings may signal the potential existence of multiple consumer segments. Such information may prompt additional managerial attention, and could initiate a more focused and segment-based marketing program.

As will be demonstrated in this paper, using the existing approaches for obtaining the shape of the distribution of consumer satisfaction ratings often results in ambiguous and unreliable interpretations of the data. Therefore, in this paper, a new approach for estimating the shape of the distribution of consumer satisfaction ratings will be introduced. The proposed approach, based on an established non-parametric method in econometrics, is shown to have superior properties to existing approaches used for graphing consumer satisfaction response distributions. Benefits of the proposed approach are demonstrated and replicated in two different consumer satisfaction settings.

IMPORTANCE OF CONSUMER SATISFACTION DISTRIBUTIONS

From an applied survey research point of view, the appropriate understanding of the shape of the distribution of consumer satisfaction responses is a valuable undertaking for three key reasons:

First, the distribution of consumer satisfaction responses in a satisfaction survey can reveal information about underlying consumer segments: The estimation of consumer satisfaction distributions is useful to any survey-based consumer satisfaction study. The knowledge of the shape of this distribution is critical in assessments made regarding the existence of multiple consumer segments. A highly dense area in the distribution of the satisfaction ratings would represent a high concentration of consumers. For example, if the distribution of the consumer satisfaction measure is multi-modal or highly dense in certain regions of the response scale, multiple consumer segments may potentially exist. Such graphical inspections can aid one in identifying the relevant market segments. A study by Kumar and Rust (1989) on managers' preferences for various segment identification methods has in fact shown that practicing managers find the graphical approach of inspecting response distributions to be the most convenient way of assessing the existence of underlying segments in the market place. The authors argue for the preferred use of graphic methods since alternative segment identification methods, such as cluster analysis, and AID (Automatic Interaction Detection), rely to a large extent on the technical sophistication of the manager.

Second, the popular use of survey methods in consumer satisfaction research: Academics and practitioners have for a long time relied on survey methods in collecting consumer satisfaction data. In academia, from the earlier works of Oliver (1980) to the more recent ones (e.g., Fornell 1992; Anderson and Sullivan 1994), consumer surveys have served as a primary source of consumer satisfaction information. Industry's use of surveys in consumer satisfaction research has especially witnessed a growth in recent years (Advertising Age 1993), and many corporations are now developing employee compensation schemes based on factors related to customer satisfaction. For example, between 1992 and 1995 alone the number of companies using customer satisfaction as a basis of employee compensation grew five fold (Romano 1995).

Third, the need for better understanding segment based differences in consumer satisfaction: Understanding the shape of the distribution of consumer satisfaction ratings also facilitates the study of the largely ignored notion of heterogeneity in consumer satisfaction research. As both Yi (1991), and Iacobucci et al. (1992) assert, consumer satisfaction research needs to place more focus on the varying satisfaction dynamics across consumer segments. As Iacobucci et al. (1992) suggest, "to account for a richer variety of phenomena, reasonable models of evaluations (quality and/or satisfaction) should also explicitly incorporate some rather fundamental concepts -- like segmentation" (p. 22).

A DEMONSTRATION OF THE PROBLEM AT HAND

Using an example, we will now proceed with a demonstration of the typical problem one faces when attempting to estimate the distribution of consumer satisfaction responses. The consumer satisfaction data utilized for this example were obtained through a survey of 315 graduate business students at an East-coast educational institution. The survey, which was conducted as part of a standard annual satisfaction study, had yielded a response rate of 63% and covered various questions about the services provided at the institution. Five satisfaction-related questions, rated on a scale of 1 to 10 (with 10 being the positive end), were obtained and utilized:

Item 1: My overall assessment of the school is (very negative ... very positive).

Item 2: Considering all the services and facilities provided by the school, I am (very dissatisfied ... very satisfied).

Item 3: Considering the cost of attending this school, it is (not a good value ... a very good value).

Item 4: My decision to attend this school has left me (very dissatisfied ... very satisfied).

Item 5: The time spent at this school has left me (unhappy ... happy).

The above five variables were input into factor analysis, which yielded one factor based on the eigenvalue > 1 criterion. The satisfaction scale was therefore constructed by taking an average of the above measures for each respondent. The resulting scale yielded a high degree of measurement reliability, as reflected by a coefficient alpha of 0.92.

Once the satisfaction data have been gathered, one needs to assess the shape of the distribution of the satisfaction measure. The most common way of estimating distributions is the histogram (Silverman 1986). A histogram is defined by an origin and a bin width. Given the origin and the bin width, a series of bins are then defined by consecutive intervals, and the histogram is constructed by graphing the percentage of responses which fall into the bins. The histogram provides an estimate of the distribution by presenting the percentage of observations which fall into each bin. In constructing a histogram one needs to make two choices: (1) a choice of the origin, and (2) a choice of the bin width. The shape of the histogram therefore primarily depends on these two decisions.

While the choice of bin width determines the degree of smoothness in the histogram, the choice of the origin determines the reference point, based on which consecutive bins are defined. As a result, depending on one's chosen value for the origin and the bin width, drastically different distributions may result. The choice of one bin width or origin over the other may therefore significantly influence one's assessment of the shape of the distribution of the satisfaction ratings. Figure 1 provides a histogram of the consumer satisfaction measure. With its origin at 5, and a bin width of 1 unit, Figure 1 suggests that the consumer satisfaction measure's distribution is uni-modal and slightly skewed to the right. However, a simple change of the bin width from 1 to 0.75 produces Figure 2, which suggests that the consumer satisfaction distribution is actually multi-modal. Figure 3 shows a similar effect resulting from a bin width of 0.5. At this point, one is left with contradicting interpretations of the exact same data, one suggesting the potential of multiple consumer segments, and the others refuting it.

An alternative approach to histogram building is the parametric approach. In this approach, one assumes that the sample data are drawn from a population with a particular distribution function. The sample data are then used to estimate the parameters of that distribution function. While the parametric approach to density estimation is computationally convenient, as we will see shortly, its main draw-back is that it constrains the shape of the estimated distribution to the one assumed by the researcher. Meanwhile, unless sufficient prior information exists, forcing a particular functional form on the distribution of satisfaction measures is both conceptually flawed and practically inappropriate.

Two commonly used distribution functions are

Figure 1
Consumer Satisfaction Histogram
(Origin=5, bin width=1)

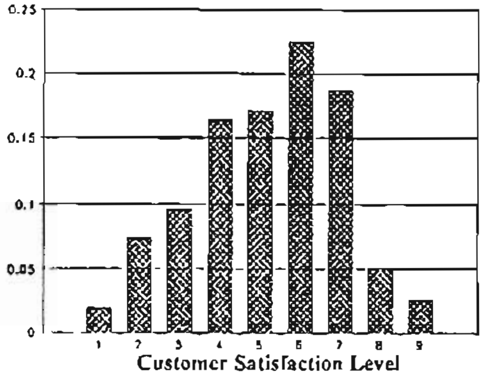


Figure 2
Consumer Satisfaction Histogram
(Origin=5, bin width=0.75)

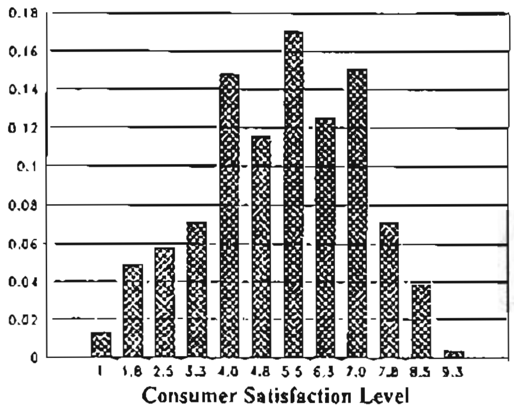
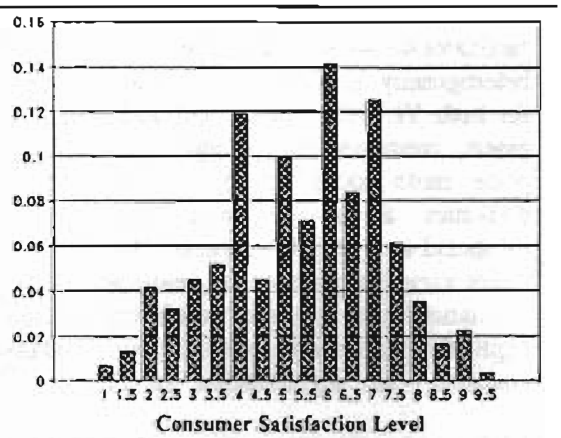


Figure 3
Consumer Satisfaction Histogram
(Origin=5, bin width=0.5)



the normal and the beta. As can be seen in the Appendix, both of these distributions are two-parameter distributions. Figure 4 shows the estimated normal distribution for the consumer satisfaction data mentioned in the previous section. As can be seen, much of the details of the data seem to have vanished. Specifically, due to the uni-modal nature of the normal distribution, the suggested high-density area in the 6-7 range of Figure 1 has disappeared. Also, due to the symmetric nature of the normal distribution, skewness in the data can no longer be observed. In order to assess the appropriateness of using the normal distribution on the consumer satisfaction data, the Shapiro-Wilk test was conducted. The results of the test rejected the null hypothesis of normality at the $p<0.0001$ level, thereby confirming that the data are not drawn from a normal distribution. Therefore, the normal approximation seems to be an inappropriate representation for the distribution of consumer satisfaction data. This observation is in fact consistent with observations made by Peterson and Wilson (1992), that most consumer satisfaction data have significant deviations from normality.

An alternative distribution function is the beta distribution. The advantage of the beta distribution over the normal distribution is that it can take on many different forms, such as a U or an inverted U, and can also be nonsymmetric. As a result, it is a convenient distribution function for many marketing and social science applications (e.g., Morrison 1981; Heckman and Willis 1977; Sabavala and Morrison 1981). However, as in the case of the normal distribution, the beta distribution is also constrained in its shape in that, with the exception of a U or J shape, it is unable to reflect other cases of multi-modality in the data. It too is therefore limited in its application to consumer satisfaction data, where multi-modality in consumer responses is likely. Figure 5 shows the estimated beta distribution using the consumer satisfaction data mentioned earlier. Again, as in the case of the normal distribution estimate, much of the detail has disappeared due to the shape of the distribution function enforced by the beta distribution.

Figure 4
Consumer Satisfaction Density Estimate
Normal Distribution

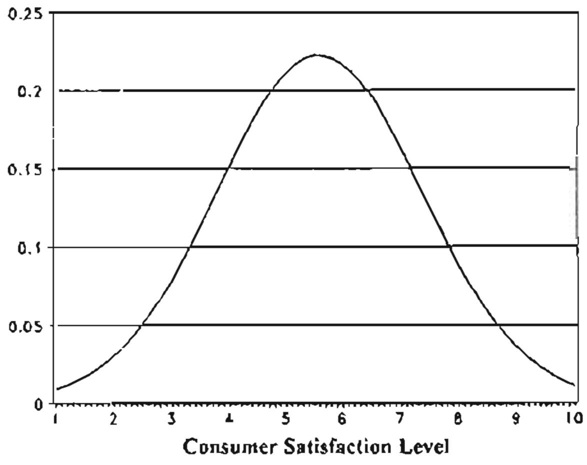
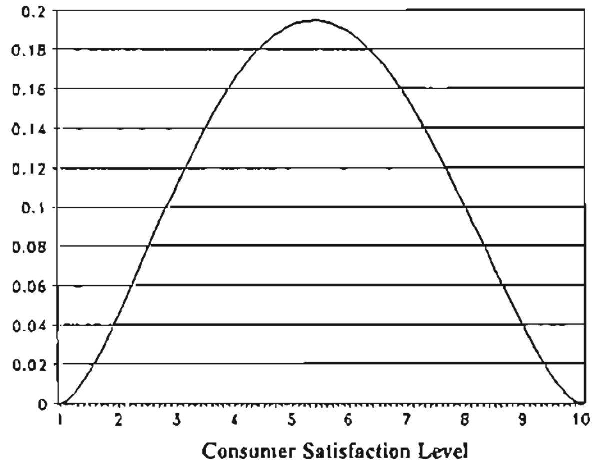


Figure 5
Consumer Satisfaction Density Estimate
Beta Distribution



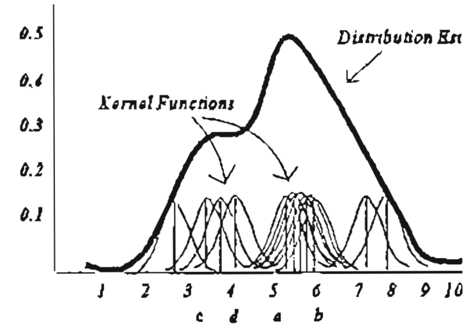
THE PROPOSED METHOD: KERNEL ESTIMATION

Since the existing methods are unable to reflect subtle fluctuations in consumer satisfaction responses, a more flexible method for estimating consumer satisfaction distributions is needed. In this section, the kernel estimation method is introduced as an approach to obtaining estimates of the underlying distribution of the consumer satisfaction measures. Kernel estimation is a well-established non-parametric approach to estimating distributions. It is the most commonly used non-parametric distribution estimation method and has seen wide usage in a variety of applications in economics. Among its many advantages is the fact that it relaxes the restrictive assumption that the observed data are drawn from a given parametric distribution. The relaxation of the parametric assumptions is especially appealing in applications involving consumer satisfaction data, as prior assumptions about the shape of the distribution of consumer responses can often significantly restrict the shape of the estimated distribution. In addition, kernel estimation provides much more stable results than those obtained through histograms (Silverman 1986).

Prior applications of kernel estimation in the marketing literature are limited. Rust (1988) introduced the concept of flexible regression to the marketing literature, using the kernel method as a means for relaxing many of the restrictive assumptions of classical regression. Abe (1991) further advanced Rust's work by introducing the moving ellipsoid estimation method. Donthu and Rust (1989), in an interesting application of the method, used the kernel method to estimate the geographic distribution of a city's population. Having determined the shape of the distribution, they then identify the optimal location for a new retail outlet. In a later work, Donthu (1991) applied kernel density estimation in order to estimate market area densities, and Abe (1995) applied the method for studying consumers' brand choice behavior.

Conceptually, the kernel estimation method is actually quite simple. The kernel density estimate at a particular point x is simply the sum of n individual 'kernel' functions. The value of each of these n kernel functions depends on the distance between x and the observations around it. If x is close to many observations, the kernel functions are set up such that the value of the individual kernel functions are large, and therefore their sum is large. As a result if x is located in a densely populated portion of the scale, the distribution would end up being "bumped up." In contrast, if x is far from most sample observations, the individual kernel function values are small, resulting in a low distribution estimate at x. Figure 6 graphically demonstrates the basic concept, and the Appendix presents the technical details. The horizontal axis in Figure 6 shows the satisfaction response scale. Each point on the horizontal axis represents a single observation from a respondent. Therefore, all the dots on the horizontal axis reflect the entire sample of consumer satisfaction responses in the survey. For example, the point "a" is the observation for one respondent (having a response of 5) and point "b" is another observation for another respondent (having a response of 6). The vertical axis represents the density of the distribution of observations. For example the area between points a and b has a large bump because there are many observations in this area. On the other hand the area between c and d has a drop in the distribution, because there are very few observations in this region of the scale.

Figure 6
Demonstration of Kernel Method

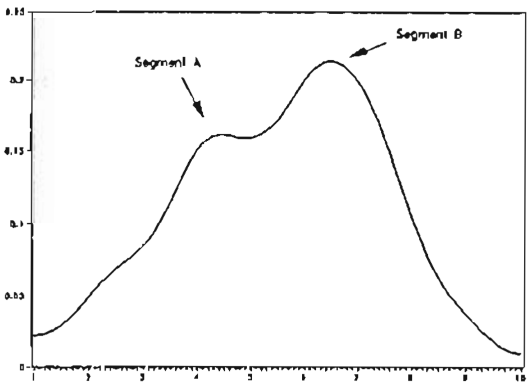


What makes kernel estimation such a useful technique is some of its attractive statistical properties. Specifically, given a sufficiently large sample size, we are guaranteed to obtain a distribution estimate which closely resembles the true distribution of the measure in the population, as the kernel estimate has also been shown to be both consistent and unbiased (Rosenblatt 1956; Parzen 1962).

ESTIMATION

Kernel estimation of the distribution of the satisfaction ratings in the survey was achieved using the Gauss programming language. Total estimation time with an Intel 486-33 processor was under 45 seconds. Figure 7 graphically presents the kernel estimate of the satisfaction measure. Contrasted against Figures 1 and 2, visual inspection of Figure 7 shows the existence of two highly dense regions, one centered at 4.3, and the other at 6.5. Moreover, contrasted against Figures 4 and 5, the kernel estimate suggests that the estimated distribution does not look anything like a beta or a normal distribution.

Figure 7
Consumer Satisfaction Distribution Using Kernel Estimation



Consumer Satisfaction Level

In the following sub-sections, the merits of the kernel method will be discussed on three grounds: (1) the ability of the kernel estimate to fit the original data, (2) the ability of the method to identify consumer segments, and (3) the managerial implications of the findings.

Superior Fit

In order to assess the relative fit of the various approaches, the consumers' responses were randomly split into two samples. An estimation sample of 150 respondents was used to estimate the consumer satisfaction distribution using the various methods. The remaining 165 respondents' data were then used as a hold-out sample. The cumulative distribution of the resulting estimates were then compared to the cumulative density of the hold-out sample using the goodness of fit index (GFI) described in the Appendix. Table 1 shows the results of the fit test. As can be seen from the table, and as expected, the kernel density estimate produced the best fit to the hold-out sample data. This was followed by the two parametric estimates. The worst fit was obtained using the histogram.

Table 1
Goodness-of-Fit Index

Estimation Method	Goodness of Fit Index (GFI)
Kernel	18.52
Normal	11.41
Beta	3.03
Histogram (origin=5, bin width=1)	2.10

Segment Identification Ability

Since the kernel distribution estimate is an unbiased and consistent estimator of the underlying distribution (Silverman 1986), one can reasonably conclude that the fluctuations observed in the distribution graph are likely to be due to the underlying distribution of consumer satisfaction. Visual inspection of the resulting kernel estimate indicates two consumer segments, one with satisfaction levels centered at 4.3 (referred to as segment A), and another with satisfaction levels centered at 6.5 (referred to as segment B), with the midpoint separating the two segments. To further establish the existence of these segments, it is preferable to demonstrate that the two identified segments are conceptually different from one another in some managerially meaningful way. This may therefore help guide further managerial actions. It may also help address the largely ignored notion of consumer heterogeneity in consumer satisfaction research and the possibility that consumer satisfaction dynamics might vary from one consumer segment to another (Yi 1991).

In order to do so, in addition to the satisfaction measures, the survey had also obtained measures of the performance of the institution on individual aspects of its services. These include performance perceptions of the student service offices, the physical facilities, the administration, and teaching quality. These measures were obtained in order to assist the management in identifying areas where quality improvement initiatives can be directed. The items in the scales were developed based on management input, followed by a set of pre-tests, and are outlined in Table 2. As can be seen from the table, the multi-item scales all provide highly reliable measures, reflected by coefficient alpha values of 0.74 and higher.

Table 2
Multi-item Scales Used in the Survey
(All items on a 1-10 scale)

Physical Facilities: Coefficient alpha = 0.74
Room availability for group projects and meetings (low...high)
My desire to spend more time in the building (low...high)
The cleanliness of the building (low...high)
The overall quality of the building's facilities (low...high)

Student Services: Coefficient alpha = 0.80
The usefulness of the Career Resource Center in my job search (low...high)
The professionalism and courtesy of the Placement Office (low...high)
The ability of the Placement Office in bringing in a variety of companies (low...high)
The ability of the Placement Office in bringing in a large number of companies (low...high)
The overall quality of the school's student services (low...high)

Administrative Offices: Coefficient alpha = 0.89
The dean's office's effort in improving the quality of student life (low...high)
The honesty and openness of the administration (low...high)
The availability of the administration to discuss student issues with students (low...high)
The administration's follow-up of issues that are presented by students (low...high)
The Admissions Office's ability to present a true picture of the school to prospective students (low...high)

Teaching Quality: Coefficient alpha = 0.87
The level of quality of the teaching by professors is (low...high)
The accessibility of professors for questions outside of class (low...high)
The overall level of satisfaction with the teaching approach (low...high)

One possible way in which the two identified segments might vary is in the way the dynamics of the satisfaction process function. In other words, the way consumers form their satisfaction evaluations, based on the individual components of the service, may vary between the two segments. In order to test the above assertion, a standardized regression analysis was conducted on the obtained measures. Specifically, the satisfaction measure was regressed on the component level performance measures outlined in Table 2 (i.e., physical facilities, student services, administration, and teaching quality). The analysis was conducted separately for each segment, and the standardized coefficients were then used to gain insights on the varying satisfaction dynamics between the two segments. Table 3 presents the results of this analysis.

Table 3
Segment-Level Estimates of the Consumer Satisfaction Model
(numbers in parentheses are standard errors)

Service Component	Standardized Beta's Segment A	Standardized Beta's Segment B
Physical Facilities††	0.187**	0.088
	(0.079)	(0.076)
Student Services††	0.128	0.002
	(0.085)	(0.079)
Adminstration†	0.141	0.162*
	(0.084)	(0.079)
Teaching Quality††	0.341**	0.256**
	(0.078)	(0.076)

††Segment differences significant at the $p<0.01$ level
†Segment differences significant at the $p<0.05$ level
*Coefficient significant at the $p<0.05$ level
**Coefficient significant at the $p<0.01$ level

As can be seen from the results, the two segments vary in their satisfaction dynamics. For segment A respondents, teaching quality and the physical facilities are the strongest driver of satisfaction, reflected by the high t-values. Student services and administration do not seem to have any significant influence on the satisfaction ratings of this segment. For segment B, on the other hand, the effect of teaching quality on satisfaction is considerably lower, and the effect of the physical facilities is negligible. In contrast to segment A, for segment B respondents, the perceptions of the administration are a significant driver of satisfaction.

Figure 8
Consumer Satisfaction Density for Retail Outlet
Using Kernel Estimation

Managerial Implications of the Findings

From a marketing management perspective, the above findings suggest that in order to improve consumer satisfaction levels, the management may need to consider addressing the two segments in different ways. Moreover, the management can prioritize and focus quality improvement efforts based on which consumer segment is considered to be more important to serve. For example, addressing segment A consumers would clearly require improvements to the physical facilities and improved teaching quality. On the other hand, while improvements in teaching quality would also improve segment B's satisfaction level, addressing the needs of this segment would also require improvements in the perceptions of the administration. Physical facility improvements would not significantly improve this segment's satisfaction ratings. Based on the expected costs and benefits of each of these improvements, the management can therefore proceed to develop an optimal quality improvement program.

REPLICATION

In order to further test the proposed method, a replication of the previous analysis was done on consumer satisfaction survey data obtained from a very different service setting: a retail outlet. The retail outlet is part of a regional chain of fast food convenience stores, which sell grocery items, beverages and fast food. The consumer satisfaction data utilized were obtained from a standardized survey done in order to assess consumer perceptions of service quality at the retail outlet. A total of 242 customers were administered the consumer satisfaction questionnaire, which assessed their perceptions of various aspects of the service, such as its cleanliness, employee responsiveness, and food quality.

As in the previous example, a multi-item scale was developed in order to obtain reliable measures of consumer satisfaction. The satisfaction scale was constructed by averaging six survey questions, each on a scale of 1 to 5 (with 5 being the positive end). The six questions were regarding (a) the cleanliness of the food area, (2) the cleanliness of the cash register area, (3) the freshness of the food, (4) the speed of preparation of the food, (5) the friendliness of the employees, and (6) the speed of service by the employees. The coefficient alpha for the scale was 0.85, and the mean satisfaction rating was 4.39.

As in the previous case, kernel estimation was done using the Gauss programming language. Figure 8 shows the resulting kernel distribution estimate. A split sample analysis found the kernel estimate to provide a fit to the holdout data superior to the alternative methods. The goodness of fit index (GFI) for the kernel was 21.29, as compared to 13.34 for the normal, 11.72 for the beta, and 14.92 for the histogram. Moreover, as can be seen, multiple consumer segments can be identified on the basis of the peaks exhibited in the distribution of the satisfaction measure. A highly satisfied group of consumers can be observed in the 4.2-5.0 portion of the response scale (Segment B), as indicated by the peaks. Moreover, a low satisfaction segment can be found in the sub 4.2 region of the scale (Segment A).

To assess the difference between the two segments, standardized regression was conducted to examine the relative impact of the various service attributes on consumer behavior. To do so, data obtained from scales assessing the rating of employees, the quality of the food, and the cleanliness of the retail outlet were used. Table 4 outlines the items used to develop these scales. A standardized regression analysis for each segment was conducted. The dependent variable used was consumers' self-reported level of frequency of visiting the retail outlet. Table 5 shows the resulting standardized beta coefficients for the two segments.

As can be seen, segment B's behavior seems to be mostly affected by perceived food quality. On the other hand, segment A seems to be less sensitive to food quality. For this segment, the cleanliness of the outlet and employee responsiveness seem to be more important. The two segments are further differentiated based on their demographics. The high satisfaction segment, Segment B, is mostly made of males. Males account for 60.8 % of respondents in this segment. On the other hand, the low satisfaction segment is equally represented by the two sexes.

Table 4
Multi-item Scales for Service Quality Components

Cleanliness (Coefficient Alpha = 0.90)
- Cleanliness of the Sidewalk
- Cleanliness of the Parking
- Cleanliness of the Coffee Area
- Cleanliness of the Fountain
- Cleanliness of the MTO
- Cleanliness of the Cash Register
- Cleanliness of the Rest Room

Employees (Coefficient Alpha = 0.86)
- Employee Friendliness
- Employee Speed
- Employee Appearance

Freshness of the Food (Coefficient Alpha = 0.80)
- Speed of Food Preparation
- Cleanliness of Food Preparation Employees
- Freshness of the Coffee

Table 5
Replication: Segment-Level Estimates of the Consumer Satisfaction Model (numbers in parentheses are standard errors)

Service Component	Standardized Beta's Segment A	Standardized Beta's Segment B
Employees†	0.21	0.17
	(0.11)	(0.21)
Food Quality††	-0.02	0.27*
	(0.15)	(0.13)
Cleanliness*†	0.19	-0.30
	(0.13)	(0.14)

†Segment differences significant at the $p<0.05$ level
††Segment differences significant at the $p<0.01$ level
*Coefficient significant at the $p<0.05$ level

The gender difference between the two segments is significant at the $p<0.1$ level. No other significant demographic differences were found between the two segments. From a managerial perspective, the above results suggest that each of these segments needs to have different marketing programs tailored to them. Improving consumer satisfaction in segment A requires improvements in the cleanliness of the outlet. On the other hand segment B may benefit from improvements in the quality of the food. Moreover, since the high satisfaction segment (segment B) has a higher proportion of males, further research on the needs of female consumers may facilitate further service quality improvements.

PROS AND CONS OF THE METHOD

It is important to note that despite its favorable statistical properties and ease of use, the kernel estimation method does have some minor drawbacks. It has for example been shown that when applied to data from long-tailed distributions, the distribution estimate in the tails may become unreliable. An alternative estimation method, called the nearest-neighbor method needs to be used in such cases (Silverman 1986, p. 19). In addition, while the kernel technique is easy to program, it is a data intensive procedure. As a result with very large samples (i.e., one thousand or more), the estimation procedure may become considerably slow. In such cases fast Fourier transforms can be applied to speed up the process (Hardle 1993). Moreover, with small sample sizes (i.e., less than a hundred), the reliability of the obtained estimates tends to be low, as shown by the simulation work of Donthu and Rust (1994). In such cases, the histogram approach is likely to be preferable.

Fortunately, the above concerns typically do not apply to most consumer satisfaction data, as consumer satisfaction response scales are limited in their range of possible values, and many consumer satisfaction surveys utilize moderate sample sizes. The proposed method is especially relevant since many consumer satisfaction studies utilize survey methods to gauge consumer satisfaction. Moreover, as shown by Kumar and Rust's (1989) study, a visual approach for detecting segments such as the one proposed here is the most preferred approach by practicing managers. As the authors argue, to utilize alternative approaches for segment identification, such as cluster analysis and AID (automatic interaction detection), "a great deal of sophistication is required to accurately interpret the results" (p. 24). On the other hand, with a method such as kernel estimation, the resulting distribution graph can easily be inspected, analyzed, and communicated, making it a useful tool for both applied and academic research in consumer satisfaction.

CONCLUSION

In this paper, we have reviewed various popular methods for estimating the shape of the distribution of consumer satisfaction ratings obtained from consumer surveys. We further offered the kernel estimation method as a tool for improving our ability to assess the shape of this distribution. In doing so, we demonstrated that kernel estimation enables us to better visualize and interpret the distribution of consumer satisfaction measures. The method is superior to the traditional approach of building histograms which is highly sensitive to one's choice of the origin or the bin width. In addition, unlike parametric estimation methods, kernel estimation does not constrain the form of the estimated distribution to a particular shape. Therefore, the kernel method allows the consumer response data to "speak for itself" in determining the shape of the distribution of consumer responses.

The application of the method on consumer satisfaction data in two separate scenarios helped identify underlying consumer segments. These segments were further differentiated based on the dynamics by which satisfaction is arrived at. As a result, the proposed method facilitates the study of heterogeneity in consumer satisfaction data, an issue of equal concern to academics and practitioners. Moreover, it facilitates the development of segment-based and focused quality improvement programs in consumer services.

APPENDIX
Distribution Estimation and Comparison Approaches

Normal Distribution:
Formally, the normal distribution at a point x is defined by:

$$f(x)=\frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2}$$

where μ and σ are the population mean and standard deviation, respectively. The normal distribution has a symmetric and uni-modal shape. Moreover, it ranges from minus infinity to positive infinity.

Beta Distribution:
The beta distribution on the other hand, can take on a variety of shapes. The beta distribution at a point x is defined by:

$$f(x)=\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha).\Gamma(\beta)}x^{\alpha-1}(1-x)^{\beta-1} \quad for \quad 0<x<1;$$

where α and β are the distribution parameters. Depending on the values of α and β a variety of distribution shapes, including U, inverted U, J, and inverted J can be produced. Moreover, in contrast to the normal distribution, the range of values which x can hold is bounded.

Estimation of Distribution Parameters:
For both the normal and beta distributions, parameter estimation can be achieved through maximum likelihood estimation or the method of moments. In this paper, the method of moments was used due to its computational convenience (Freund and Walpole 1980). Using the method of moments, the first and second moments of the sample are set equal to those of the distribution and the pair of equations are solved in order to determine the distribution parameter values.

Kernel Density Estimation:
Formally, the kernel density estimate at a point x is defined by:

$$\hat{f}(x)=\frac{1}{nh}\sum_{i=1}^{n}K\left(\frac{x-x_i}{h}\right),$$

where n is the sample size, h is the smoothing parameter, K is the kernel function, and the x_i are the data points. In order to conduct kernel estimation, one has to choose both a kernel function K, and a smoothing parameter h. Often the kernel function is chosen such that it is non-negative, symmetric and integrable to 1. Many choices of the kernel function, such as the normal, the Epanechnikov, and the uniform exist. Interestingly, it has been shown that the choice of the kernel function, even with small sample sizes, does not greatly affect the resulting kernel estimate (Silverman 1978).

The smoothing parameter h is also chosen such that as $n \to \infty$, $h \to 0$. The correct value of the smoothing parameter is pre-determined such that it minimizes the expected error in the distribution estimate and is approximated by (Silverman 1986, p.45):

$$h_{opt}=\left(\frac{4}{3}\right)^{1/5}s\ n^{-\frac{1}{5}}$$

where s is the standard deviation of the measure in the sample, and n is the sample size.

Goodness of Fit Comparisons:
In order to compare the performance of the various distribution estimates (e.g., normal, beta, histogram, and kernel), a goodness-of-fit index expressed by:

$$GFI=\frac{1}{\int_L^U [F_{estimate}(x)-F_{sample}(x)]^2\,dx}$$

was used, where $F_{estimate}(x)$ and $F_{sample}(x)$ are the cumulative distribution functions at point x of the distribution estimate and the sample, respectively, and L and U represent the lower and upper bounds of the scale. The higher the index, the better the fit. The intuition behind this fit measure is that a good fit would result in a cumulative distribution estimate which closely follows the actual distribution of the hold-out sample. As a result, the better the fit, the smaller the denominator, and the higher the GFI.

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