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MARKET SEGMENTATION
A Neural Network Application

Jonathan Z. Bloom
University of Stellenbosch, South Africa

Abstract: The objective of the research is to consider a self-organizing neural network for segmenting the international tourist market to Cape Town, South Africa. A backpropagation neural network is used to complement the segmentation by generating additional knowledge based on input–output relationship and sensitivity analyses. The findings of the self-organizing neural network indicate three clusters, which are visually confirmed by developing a comparative model based on the test data set. The research also demonstrated that Cape Metropolitan Tourism could deploy the neural network models and track the changing behavior of tourists within and between segments. Marketing implications for the Cape are also highlighted. **Keywords:** segmentation, SOM neural network, input–output analysis, sensitivity analysis, deployment. © 2005 Elsevier Ltd. All rights reserved.

Résumé: Segmentation du marché: une application du réseau neuronal. Le but de la recherche est de considérer un réseau neuronal auto-organisateur pour segmenter le marché touristique international à Cape Town, en Afrique du Sud. On utilise un réseau neuronal de rétropropogation pour compléter la segmentation en générant des connaissances complémentaires basées sur une relation input–output et des analyses de sensibilité. Les résultats du réseau neuronal auto-organisateur indiquent trois groupes qu'on confirme visuellement en développant un modèle comparatif basé sur l'ensemble des données d'essai. La recherche a montré aussi que le Tourisme Métropolitain du Cap pourrait utiliser les modèles de réseau neuronal et suivre la trace du comportement changeant des touristes dans et entre les segments. On souligne aussi les implications de marketing pour le Cap. **Mots-clés:** segmentation, réseau neuronal, analyse input–output, analyse de sensibilité, utilisation. © 2005 Elsevier Ltd. All rights reserved.

INTRODUCTION

Marketing an international tourism destination such as Cape Town in South Africa has never been more dynamic, competitive, and important than it is today. Successful marketing requires careful planning and comprehensive analysis of data and information obtained from tourists that frequent destinations and those that do not. There is no shortcut to establishing a positioning strategy that could deliver a valuable experience to tourists.

The ability to identify and serve tourists and create a dialogue with them has become a necessity for destination organizations such as

Jonathan Bloom (Department of Business Management, University of Stellenbosch, Matieland, 7602, South Africa. Email <jzb@sun.ac.za>) has a particular research interest in the application of predictive modeling in tourism using artificial intelligence technology. He spent several years in the private sector assisting destination organizations such as South African Tourism and Cape Metropolitan Tourism to extract more value from the data obtained from market surveys.

Cape Metropolitan Tourism (hereafter referred to as Cape Metro Tourism). Managing the tourist relationship has become an essential part of attracting those with specific profiles to a destination. All activities around the tourist ''touch points''—which aim to identify, attract, and retain the most valuable tourists for a destination and its enterprises—should be considered. The end result is to enhance retention and loyalty and sustain growth from profitable tourists. It is important to determine what it takes to encourage them to purchase the product/service that a destination offers. A need exists to understand their behavior and thus more in-depth knowledge about the homogeneous characteristics of groups is required over and above evaluating overall arrivals, expenditure figures and trip characteristics.

Marketing strategists of destination organizations often encounter the problem of how to appropriately segment the market and package differentiated products and services for target segments. Segmentation is a methodological process of dividing a market into distinct groups that might require separate experiences or marketing service mixes (Venugopal and Baets 1994). Customer clustering is one of the most important techniques used to identify these segments (Saarenvirta 1998). Various clustering techniques are used as part of a methodology to identify segments, which become the foci of marketing strategy. The basis of this generally includes the identification and assessment of various tourist characteristics (such as demographics, socioeconomic factors, and geographic location) and product related behavioral characteristics (such as purchase behavior, consumption behavior, and attitudes towards and preference for attractions, experiences and services). Target marketing is a strategy that aims at grouping a destination's markets into segments so as to aim at one or more of these by developing products and marketing programs tailored to each (Kotler 2001).

Inadequate segmentation and clustering problems could cause a tourism destination organization, such as Cape Metro Tourism, to either miss a strategic marketing opportunity or not cash-in on the rewards of a tactical campaign. Market segmentation has developed as a methodology to identify target segments, with the outcomes of the process used to help understand tourists' relationship with the destination.

The objective of the research is to consider the use of a self-organizing (SOM) neural network for segmenting the international tourist market to Cape Town. A backpropagation (BP) neural network (based on the output provided by the former) was also used to complement the process by generating additional market knowledge about the relationship between the inputs used and the macrosegments obtained from the application of the SOM model. Input–output relationship and sensitivity analyses were used for the purpose of extracting additional market knowledge about the macrosegments.

NEURAL NETWORKS AND MARKET SEGMENTATION

The need for in-depth knowledge of segments remains an essential element of understanding the homogeneous behavior of groups of tourists. Various techniques have been used for market segmentation in tourism, which range from elementary percentiles and quartiles to more complex multivariate techniques such as factor analysis, principle components, and cluster analysis (Galloway 2002; Jang, Morrison and O'Leary 2002; Mok and Iverson 2000). Current segmentation methodologies and clustering techniques have evolved to include the use of artificial neural networks for segmenting markets.

Examples of studies using artificial neural networks have included Mazanec (1992), who used a SOM neural network to conduct a market segmentation of Austrian tourists. A segmentation of senior tourists in Western Australia was performed using self-organizing feature maps (Kim, Wei and Ruys 2003). Artificial neural networks have also been applied in other areas of tourism management and marketing such as to predict tourist choice activity, forecast tourist behavior, forecast demand, and analyze guest loyalty (Jeng and Fesenmaier 1996; Law and Au 1999; Pattie and Snyder 1996; Tsaur, Chiu and Huang 2002).

Artificial neural networks are often compared to traditional multivariate techniques (such as multiple linear regression) as a means of benchmarking linearity vs. nonlinearity of a data set. Generally, artificial neural networks are superior to linear techniques when compared in terms of accuracy. However, this is possibly not unusual, as the universal approximation theorem introduced by Hornik, Stinchcombe and White (1989) suggests that a properly trained artificial neural network can never be worse than a linear classifier. Although artificial neural networks also have limitations in respect of explanation, they offer advantages in terms of learning ability, flexibility, adaptation, and knowledge discovery (Goontilake 1995). An assessment of several primary distinctions between BP neural networks and multiple linear regression indicate that the former are nonparametric in the sense that a functional form need not be specified a priori, while prior knowledge and specification of a functional form is required for multiple linear regression. BP neural networks adapt their weights as new input data become available, thereby readily adjusting to a changing environment. Multiple linear regression is not generally adaptive, but typically processes all the data once again if new data is added. However, multiple linear regression could in principle be defined as an adaptive model if coupled to matrix updating routines. BP neural networks perform well on nonlinear/chaotic data by deriving a suitable map between high dimensional input pattern space and output. Multiple linear regression generally assumes a linear relationship between the independent and dependent variables and relates the former directly to the latter, whereas BP neural networks relate indirectly by determining the weights between units among layers. This performs well with missing or incomplete data due its fault tolerant nature and ability to generalize across gaps. The presence of missing values in a data set generally requires the exclusion of an entire observation or the exclusion of the variable for all observations if multiple linear regression is considered (De Tienne and Lewis 2003).

It may also be argued that nonlinear or nonparametric regression techniques (like logistic regression) may provide a more appropriate and direct comparison with BP neural network models. It should be noted that logistic regression, for example, which is a powerful modeling tool, assumes that the response variables (the log odds, not the event itself) are linear in the coefficients of the predictor variables. Conversely, neural networks use the hidden layers to estimate the form of the nonlinear relationship between the input and output neurons and the interaction in a semi-automated way (Two Crows 1999).

Conventional cluster analysis has been applied across various industries and used for a variety of applications. A SOM neural network, however, which is also used for clustering, appears to offer some benefit over conventional cluster analysis. Mazanec (1999, 2001) holds that the topology-preserving properties of a SOM neural network distinguish it from conventional clustering methods. It assigns inputs to a series of partitions on the basis of similarity of their expression vectors to reference vectors defined for each partition. It is the process of defining these reference vectors that distinguishes this modeling approach from, for instance, *k*-means clustering, an algorithm often used in conventional cluster analysis. Notwithstanding, should the neighborhood parameter of a SOM neural network be set to zero, which is not the case in this research, no neighborhood update is performed, which makes it equivalent to conventional cluster analysis, and implies that the solution is optimal in terms of the partitioning of minimum variance. Conversely, specifying a neighborhood parameter above zero also implies that a minimum variance result is not obtained. However, the preservation of the topological ordering of the nodes would be negated if the neighborhood parameter were set to zero. It is generally this trade-off that a researcher should make, while also considering the practical implications of using the SOM approach and the objectives of the market segmentation. Consequently, the self-organizing feature map illustrates microsegments (or nodes) and offers an automatic indication of which microsegments to merge in order to achieve macrosegments (combination of nodes).

Media planners and marketing strategists of tourism destination organizations would welcome this approach from a practical perspective, as they are able to view the microsegmentation and be guided as to which microsegments to disaggregate in order to develop macrosegments. Furthermore, this modeling approach also has the ability to combine vector quantization (clustering of tourists) with topological ordering (the mapping of tourist characteristics), and is also an attractive proposition due to its ability to operate on a very large sample (Mazanec 1995). The attractiveness of the methodology from both a scientific viewpoint and its practicality for reviewing microsegments, which could be disaggregated to form macrosegments, provided the rationale to consider the use of an SOM neural network to achieve the objectives of this study.

Nature of SOM Neural Networks

A SOM neural network is a simplified model of the feature-to-localized-region mapping of the brain from which it derives its name. The architecture is quite simple. It consists of a group of geometrically organized neurons in one, two, three, or even higher dimensions. One novel aspect of the network's learning mode is that no feedback from the environment will be provided during learning. The network must discover for itself topological properties of interest that may exist in the input data. The measure of similarity is the Euclidean distance between the responding neurons arranged in regular geometrical arrays. Examples of this type of learning are Adaptive Resonance Theory and Kohonen Self-Organizing Feature Maps (Kohonen 1997).

A typical neural network consists of a number of simple processing elements called neurons. Each neuron is connected to other neurons by means of directed communication links, each with an associated weight. The weights represent information being used by the network to solve a mapping problem. Figure 1 illustrates an example of the mapping structure for a SOM neural network. The architecture is based on the understanding that the representation of data features might assume the form of a self-organizing feature map that is geometrically organized as a grid or lattice. In the pure form, the model defines an ''elastic net'' of points (parameter, reference, or codebook vectors) that are fitted to the input data space to approximate its density function in an ordered way. The algorithm takes a set of N-dimensional objects as input and maps them onto nodes of a two-dimensional grid, resulting in an orderly feature map as indicated in Figure 1 (Kohonen 1997).

Unsupervised learning can only be implemented with redundant input data. Redundancy provides knowledge about statistical

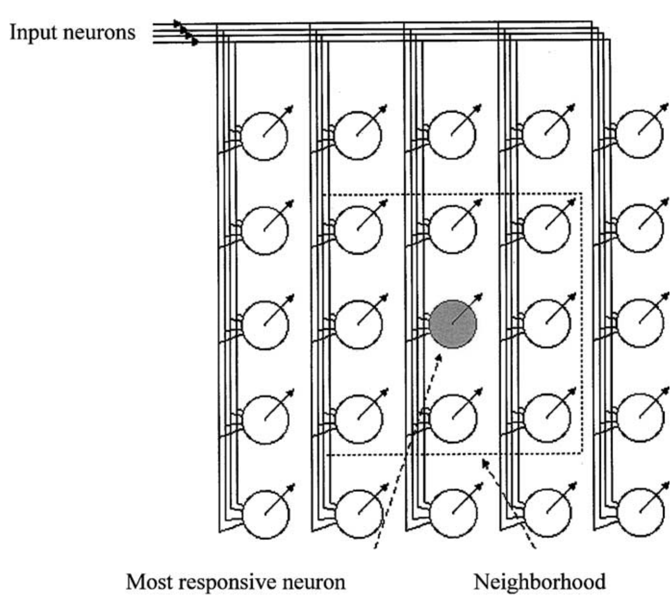

Figure 1. The Structure of a SOM Neural Network

properties of input patterns. In the absence of target responses or guidelines, the network can, for example, classify, recognize, or map input data during a process of competitive learning. Kim et al (2003) indicate that the winning output node will receive the only reward during learning in the form of a weight adjustment. The whole process is driven only by repeated representations of the input vectors and the applied learning rule. The process begins with all network weights initialized to a small random value. Training proceeds by repeatedly exposing the network to the entire set of input vectors. The Kohonen layer computes the distances between the weight vector for each of the neurons and the input pattern. The neuron that is closest (minimum distance) is the ‘‘winner’’. The continued presentation of the input neurons to the network during each iteration is indicated in:

$$m_{i(t+1)} = m_i(t) + \alpha(t)h_{\mathrm{ci}}(t)[\chi(t)m_{i(t)}] \quad \forall i \in \{0, 1, \ldots\ldots, N-1\} \qquad (1)$$

where $t+1$ is the following iteration; N is the number of nodes in the network; α is the learning rate—usually a linear decreasing function over time; h_{ci} is the neighborhood kernel around the winning unit m_i and $\chi(t)$ is the input vector for the following iteration. The input vector may be drawn from the training data in a systematic or random fashion. Bek, Grosboll-Poulsen and Kristoffersen (2002) and Kim et al (2003) provide further information pertaining to the algorithm and procedure used in the Kohonen training process.

Study Methodology

The research is divided into two stages. The first stage involves the development of a SOM neural network model. The second stage involves using the specification of macrosegments obtained from the model as output for the development of a predictive BP neural network model for generating additional market knowledge in order to enhance the segmentation. Figure 2 illustrates the methodology used in the segmentation process.

The data analyzed in this paper was obtained from Cape Metro Tourism surveys of international arrivals visiting Cape Town in South Africa. This is conducted in winter and summer of each year. The collective sample of data from the three surveys used in this analysis entailed 694 respondents who frequented Cape Town during the summer of 2000 (247), winter of 2000 (202), or the summer of 2001 (245). The questions represented a broad mix of tourist trip, demographic, socioeconomic, and geographic characteristics. Types of data generated by the survey included nominal, interval, and ratio data.

The nature and scope of the three surveys differed slightly from period to period due to the inclusion of new questions and the omission of some in previous surveys. Consequently, a total of 24 variables (questions) included in all three surveys, without missing data, could be considered for inclusion in the research process. An exploratory data analysis was conducted on the selected variables to ascertain the

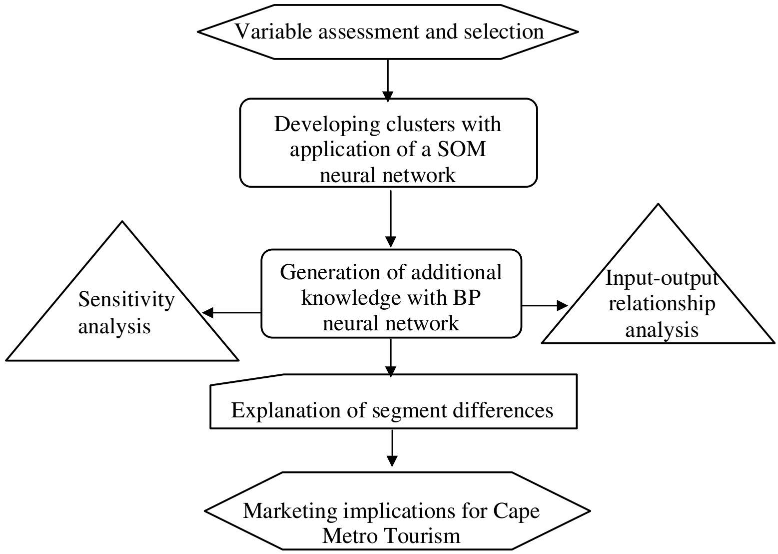

Figure 2. A Graphic Representation of the Research Methodology

distribution of the data and to identify outliers. Both Box and Whisker plots and histograms were used to visualize the distribution of the data, while several measures such as the mean, median, standard deviation, skewness, and kurtosis were used to describe the data.

The exploratory data analysis confirmed that several variables were significantly skewed, (a large number of respondents indicated a specific alternative or outlier values were present). These findings suggest that the variables may be less suitable for discriminating between the respondents. The latter aspect together with the input of Cape Metro Tourism and the local tourism industry about the existing profile of the tourists enabled the selection of the final mix of segmentation variables. Ultimately, 15 variables were selected and included in the development of the segmentation model: tourist trip characteristics (country of origin, number of days spent in Cape Town, number of visits over the past five years, total expenditure there per person); perceptions (of overall cleanliness and friendliness of residents of Cape Town as a cosmopolitan city, with diverse cultures, as another European city, as offering a variety of arts and crafts, as one city with many cultures); and demographics (family lifecycle—including family size and marital status, occupation, age and education). The software package used for part of the exploratory data analysis and the modeling procedure was Basic Modelgen (Crusader Systems 1998). The statistical software package Statistica was also used for additional exploratory analysis (Statsoft 1998). The descriptive statistics per variable included in the development of the neural network models are presented in Table 1.

Table 1. Descriptive Statistics of Input Neurons to Develop the SOM Model

Segmentation Variable	Mean	Median	Standard Deviation	Skewness	Kurtosis
Country of origin	11.17	12	6.46	0.45	−0.71
Number of visits to Cape Town in past 5 years	1.57	1	1.16	2.05	2.99
Number of days in Cape Town	10.84	6	17.14	5.23	33.60
Cleanliness of Cape Town	7.64	8	1.64	−1.24	3.08
Friendliness of Cape Town residents	8.50	9	1.31	−1.28	3.89
Cape Town as a cosmopolitan city	6.60	7	2.63	−0.20	−1.11
Cape Town a diversity of cultures	6.37	6	2.70	−0.11	−0.99
Cape Town another European city	5.21	5	3.10	−0.22	−0.91
Cape Town variety of arts and crafts	6.50	6	2.38	−0.07	−0.83
Cape Town one city with many cultures	6.33	6	2.56	−0.03	−0.91
Total expenditure	4.48	4	2.08	0.99	0.69
Age	2.90	3	1.13	0.11	−0.65
Occupation	5.37	5	3.98	0.40	−1.04
Education	4.81	5	1.11	−0.53	0.53
Family life-stage	8.83	9	4.46	0.15	−0.79

Development of the SOM Neural Network

The development of any neural network model is based on a thorough knowledge of the research problem. Blum (1992), Deboeck (1994), Masters (1993), and McCord-Nelson and Illingworth (1993) have outlined a series of steps for building an artificial neural network applicable to the development of a SOM neural network model. The eight-step procedure proposed by Kaastra and Boyd (1996), which encompasses many of the steps proposed by the abovementioned authors, is adapted as Pre-step: problem specification, business understanding, and data requirements; step 1: data collection; step 2: variable selection (number of inputs and outputs, if applicable); step 3: data preprocessing (normalizing, log transformation, standardization); step 4: selection of training, test and validation sets; step 5: Neural network training parameters and configuration values (number of input neurons, percentage iterations for constant initial learning rate, initial weights, learning rate increment, and radius decrement); step 6: neural network training (presentation of records and number of iterations); step 7: evaluation criteria (root mean square error and mean square error); and step 8: model deployment. Generally, steps 1 and 2 would be considered simultaneously prior to developing a model. However, in this instance, the survey was completed before the pre-specification of the profile attributes. Ideally, input into the nature and scope of the questions based on the research problem would occur prior to the implementation of the survey.

Data variables representing continuous data (such as total spent) were scaled to assume a value between zero and one, while nominal variables (for example, male/female) were recoded to assume values of zero or one. In this manner, the network considers each data record as continuous-valued input or binary-valued input. The data set of 694 records was randomly subdivided into training, validation, and test sets. The subdivision of the data set is based on heuristics and the principle that the size of the validation set must strike a balance between obtaining a sufficient sample size to evaluate both the training and test sets (Kaastra and Boyd 1996). The parameters and values used for training the final SOM neural network model are provided in Table 2.

The model was trained for 500 iterations and the records were presented to the network in a random manner. Note that the number of segments is not prespecified; however, the coordinates of the nodes are arranged so that the close nodes on the grid are also close in the space of the input vectors. The nodes on the two-dimensional grid (Figure 3) reflect the topological properties of the input data, while the topological organization of the units is based on the similarity between the input neurons.

Findings of SOM Neural Network Application

It was possible to distinguish three segments among international tourists visiting Cape Town. Figure 3 is an illustration of a self-organizing feature map and the three macrosegments obtained from the modeling process. Each record in the training set corresponds to a single unit, the best matching one. The learning algorithm used to form topological maps onto space with reduced dimensions (for example, from 15-dimensional input space to two dimensions) provides an idealized and visual map of the neighborhood structure. This process

Table 2. Parameters and Configured Values used for Model Calibration

Parameters	
Percentage iteration of constant initial learning rate:	1%
Learning decrement	Linear
Initial weights (%)	−0.5 (lower bound); 0.5 (upper bound)
Scaling	−0.9 (lower bound); 0.9 (upper bound)
Neighborhood radius	5
Radius decrement	Linear
Configured values	
Presentation of data	Random
Training cases	70%
Test cases	20%
Validation cases	10%
Number of inputs	15 neurons
Number of nodes	1600

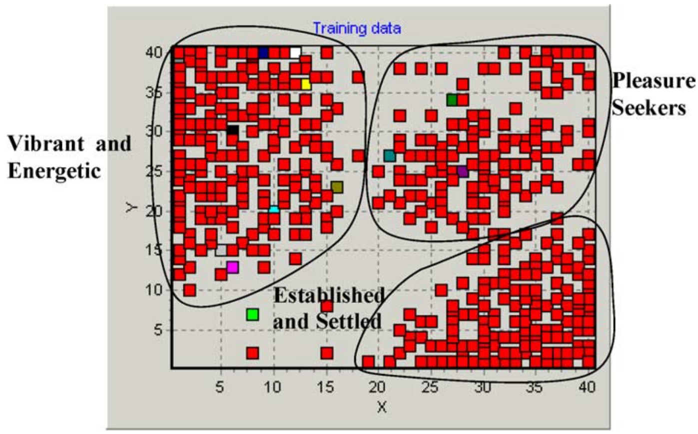

Figure 3. Macrosegments in Two-dimensional Space based on the Training

of topology preservation means that if two points are neighbors in the original higher dimensional space, they should be neighbors in the space to which the points are mapped. The squares in the two-dimensional space of the axes *x* and *y* of Figure 3 represent the data points originally observed in 15 dimensions. Very similar observations are mapped to the same *x*–*y* points, thus indicating microsegments. The SOM neural network provides the coordinates of microsegments as part of model output. For the purposes of this segmentation, the coordinates on the grid were used to visually identify the three macrosegments. A microsegment that qualifies for inclusion as part of a macrosegment should be within the visualized bounds as indicated by the latter coordinates (Figure 3). Microsegments that were not aggregated to form a macrosegment (those falling outside the visualized bounds of the macrosegments) were included as part of an applicable macrosegment based on the square of the minimum Euclidean distance. An additional self-organizing feature map was developed based on a test set of data, which represents a random sample of 20% of the original data points not used for training and validation purposes. Figure 4 is an illustration of the SOM map based on the test set of data.

It is apparent from the mapping of the respondents based on the test set of data that a similar pattern indicating the topological organization of the nodes (microsegments) emerges when compared to the training data. The findings further indicate that 39.8% of the respondents have a similar profile of attributes, perceptions, and characteristics, and are categorized as part of the Vibrant and Energetic segment. Among the remaining respondents, 34.3% have a similar profile and are grouped together to form the Established and Settled segment, while 25.9% of the respondents could be considered more or less as a homogeneous group and form part of the pleasure seekers segment.

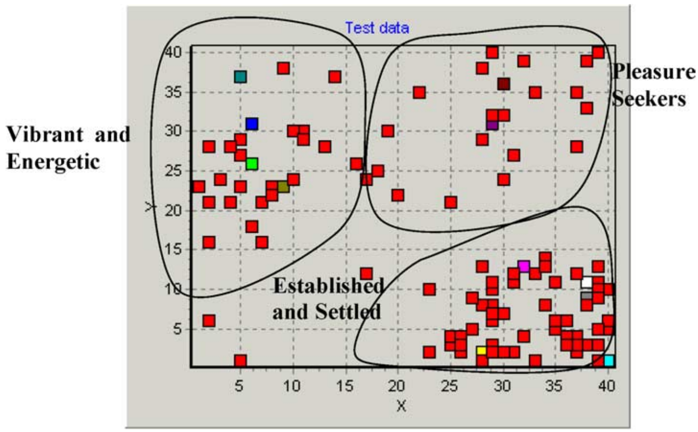

Figure 4. Macrosegments in Two-dimensional Space based on the Test Set

Profile Characteristics of the Segments

The output of the SOM neural network could be used to develop profiles for the different segments based on the 15 input neurons. The profiling of the different segments is also complemented by the input–output relationships analysis provided by the BP neural network model. Various options to describe or profile the segments could be considered. For instance, frequency tables could be developed to illustrate the percentages of each class for a specific variable. Alternatively, descriptive statistics could be used to describe the segmentation variables. Measures of central tendency and dispersion were used to determine whether or not statistically significant differences exist among the variables for each permutation of segments. The input–output relationship analysis discussed in the following section was also intended to further amplify the differences between the segments. Table 3 provides selected descriptive statistics for each of the segmentation variables, while Table 4 highlights the probability values used to determine whether or not statistically significant differences exist between the variables for each combination of segments at the 95% confidence level.

Perusal of the findings presented in Table 4 suggest that only the duration of stay in Cape Town indicates no statistically significant differences among the three segments. Notwithstanding, this variable is an important overall indicator for Cape Metro Tourism. An assessment of more specific differences between the pleasure seekers and established and settled segments indicate that education levels, the rating of Cape Town as another European city, and the country of origin do not indicate statistically significant differences. All the other segmentation variables are statistically significantly different at the 5% significance level.

Table 3. Analysis of Macrosegments using Selected Descriptive Statistics

Segment	Segmentation Variables								
	Pleasure Seekers			Established and Settled			Vibrant and Energetic		
	Mean	Median	Standard Deviation	Mean	Median	Standard Deviation	Mean	Median	Standard Deviation
Country of origin	10.15	10.5	6.25	10.94	12	6.35	12.03	12	6.59
Number of visits to Cape Town in past 5 years	1.18	1	0.55	1.75	1	1.29	1.68	1	1.27
Number of days in Cape Town	12.02	5	21.33	11.40	6	16.78	9.59	7	14.10
Cleanliness of Cape Town[a]	7.24	8	1.84	7.83	8	1.54	7.75	8	1.55
Friendliness of Cape Town residents[a]	8.06	8	1.52	8.66	9	1.20	8.66	9	1.19
Cape Town as a cosmopolitan city[a]	5.76	5	2.46	4.65	4	1.87	8.84	9	1.34
Cape Town a diversity of cultures[a]	5.62	5	2.39	4.16	4	1.58	8.77	9	1.45
Cape Town another European city[a]	5.40	6	2.82	5.52	5	2.55	4.82	5	3.63
Cape Town variety of arts and crafts[a]	5.93	6	2.06	4.89	4	1.85	8.26	8	1.74
Cape Town one city with many cultures[a]	5.57	5	2.20	4.34	4	1.53	8.55	9	1.60
Total expenditure	3.93	4	1.91	4.61	4	2.09	4.72	4	2.07
Age	1.67	2	0.52	3.69	4	0.81	3.02	3	0.98
Occupation	6.27	6	4.02	5.44	5	3.92	4.71	4	3.89
Education	4.68	5	1.10	4.71	5	1.21	4.98	5	1.00
Family lifecycle	3.82	3	1.54	12.13	12	2.99	9.25	9	3.84

[a] A rating scale of 1–10 was used to assess the variables, with 1 indicating low and 10 high.

All the segmentation variables, except the rating of Cape Town as another European city, indicate statistically significant differences between the pleasure seekers and vibrant and energetic segments at the 5% significance level, although the rating of Cape Town as another European city is statistically significantly different between the two segments at the 90% confidence level. The established and settled and vibrant and energetic segments indicate no statistically significant differences for the rating of Cape Town as a clean city and the friendliness of its residents. There are no statistically significant differences in the expenditure and the number of visits to Cape Town over the past five years. All the other variables indicate statistically significant differences at the 5% significance level, although for country of origin, the probability value is slightly higher than 5%. The findings of the input–output relationship and sensitivity analyses (discussed later), together with the assessment of statistically significant differences among the segments offer additional knowledge on an intra- and inter-segment basis.

Table 4. Differences between Combinations of Macrosegments

Segmentation Variables	Statistically Significant Differences between		
	Pleasure Seekers and Established and Settled Probability Value	Pleasure Seekers and Vibrant and Energetic Probability Value	Established and Settled and Vibrant and Energetic Probability Value
Country of origin	0.354	0.022	0.057
Number of visits to Cape Town in past 5 years	0.000	0.000	0.482
Number of days in Cape Town	0.739	0.143	0.184
Cleanliness of Cape Town	0.003	0.002	0.510
Friendliness of Cape Town residents	0.000	0.000	0.924
Cape Town as a cosmopolitan city	0.000	0.000	0.000
Cape Town a diversity of cultures	0.000	0.000	0.000
Cape Town another European city	0.622	0.070	0.012
Cape Town variety of arts and crafts	0.000	0.000	0.000
Cape Town one city with many cultures	0.000	0.000	0.000
Total expenditure	0.008	0.001	0.587
Age	0.000	0.000	0.000
Occupation	0.034	0.000	0.032
Education	0.795	0.021	0.042
Family lifecycle	0.000	0.000	0.000

Extraction of Additional Knowledge

A BP neural network model was trained using the 15 variables as inputs and three variables each representing a macrosegment as output. The model is used to extract additional knowledge and to complement the segmentation analysis by applying input–output relationship and sensitivity analyses techniques to the trained model. The classification accuracy of the model is determined by how well the training set can learn the pattern in the data when compared to the test set which comprises data not used for the purposes of training. The overall performance of the BP neural network was determined by the route mean square error (Tsaur et al 2002). The test set should be the focus when analyzing the ability of the model to generalize the learned pattern in the data. A route mean square error of 0.16 (zero would indicate a perfect match in terms of learning between the training and test data) is obtained from a comparison of the overall accuracy levels of several BP neural network models developed for the purpose of extracting additional market knowledge. A confusion matrix is used to determine how well the model was able to classify the respondents as part of the macrosegments. It assists with ascertaining the classification accuracy, which is required to ensure the validity of the extracted knowledge. The matrix compares the actual classes of the test cases to the outputs generated by the model and indicates how well the model performed the required classification on the data. An overall classification accuracy of 94.9% was obtained for the BP neural network model.

The confusion matrix also highlights the sensitivity of the respondent classification per macrosegment and is considered in support of the overall accuracy of the model highlighted above. Dividing the number of cases specified as a segment by the actual number of cases of the segment and expressing the result as a percentage indicates the sensitivity of the respondent classification per segment. Sensitivities of 92.0%, 95.5%, and 95.6% were obtained for the vibrant and energetic, established and settled, and pleasure seekers segments respectively.

As to the input–output relationship analysis, it is a technique which indicates the relationship between an output (such as the pleasure seekers segment) and a specific input (such as education level), while keeping the other inputs (independent variables) at their average levels. The input–output relationship analysis is derived from the neural network model. Each segment's output can be considered in relation to each of its input variables. Several observations from this analysis indicate that tourists from the vibrant and energetic segment indicate higher cultural, friendliness and cleanliness ratings for Cape Town than the pleasure seekers and established and settled segments. A shift in the origin countries for tourists of the vibrant and energetic segments is also apparent when compared to the pleasure seekers and established and settled segments.

As to the sensitivity analysis, it is a useful technique for determining the most influential input variables (total expenditure, education, age group, etc.) of a particular macrosegment. This analysis was computed on a global scale for country of origin, which could also be applied to any of the other 14 input variables. During a global analysis the sensitivities of the input variables obtained for the country of origin are expressed in terms of the overall sensitivity variation. Sensitivity analysis implies the perturbation of an input neuron, which results in changing the input by a positive or negative percentage, and propagating the change through the model. It is then possible to observe the change in the input variables for a specific output due to the perturbation. Note that for the purpose of this part of the analysis no input variables were perturbed. Country of origin was selected and used to indicate which variables were important attributes of a particular macrosegment. Sensitivity analysis also aims to complement the individual segment profiles by suggesting several segmentation variables which may be considered as market delineators.

In the case of the pleasure seekers segment, an average output deviation of higher than +0.006 and lower than −0.006 is used to identify market delineators. Variables that extend beyond these bounds would be considered market delineators on the basis of the boundaries specified for selection. Important attributes for tourists of the pleasure seekers segment based on the country(s) of origin are the family lifecycle, diversity of cultures in Cape Town, and the perception of it as a cosmopolitan city. The average output deviation selected for the established and settled segment is higher than +0.01 and lower than −0.01. Once again, on the basis of the country of origin, family lifecycle and diversity of cultures in Cape Town are important market delineators for tourists who form part of the established and settled segment. Market delineators for the vibrant and energetic segment based on the tourists' country of origin alluded to Cape Town's diversity of cultures and the cosmopolitan nature of the city. The average output deviation considered in the case of the vibrant and energetic segment is higher than +0.01 and lower than −0.015.

Marketing Implications for Cape Metro Tourism

The research presented in this paper offers Cape Metro Tourism an understanding of the international market that frequents this city in terms of both market clusters and mapping tourist characteristics. The marketing objectives of the destination and the available resources would dictate to what extent microsegments could be disaggregated in order to provide meaningful and actionable macrosegments for target marketing. The SOM approach could assist media planners and marketing strategists to achieve this task by providing an indication of which microsegments should be merged in order to achieve potentially actionable macrosegments. The segmentation of international tourists visiting Cape Town by means of a segmentation model, together with the subsequent input–output and sensitivity analyses, can only provide a fraction of the answer in terms of what about the segments is actionable and what would provide continued business value. The scientific basis provided by the research should be translated into market prediction goals for each of the macrosegments. Each goal should be specified with an acceptable level of detail.

The following examples could be considered as a basis from which to develop prediction goals. Tourist response: what segments would respond to an advertising campaign within three months? Repeat tourists: what targeted segments would make a repeat visit to Cape Town and register above average spending within the next year? Cross selling: what targeted segments will frequent other areas of the Western Cape province after visiting Cape Town on a previous trip? Attrition: what segments are likely not to visit Cape Town again, if follow-up marketing to these segments does not occur?

Although the SOM neural network application provides an "experimental" solution to the problem being researched in this paper, the development of actionable segments to achieve the prediction goals would provide the acid test. It is essential for the marketing strategist and media planners of a tourism destination organization to ensure that the macrosegments are substantial in terms of size to ensure that reaching them is worth the effort. This implies weighting up the different segments of the tourist population. In addition, the selected segments should be accessible (can be reached with a targeted message) and durable (last long enough to cultivate and harvest). Probably the primary criterion for an acceptable segmentation both in academic and practical terms would be whether or not the segments could be profiled in measurable and actionable terms and to what extent they could be characterized with appropriate demographic, socioeconomic, and media-use pattern information. Notwithstanding the importance of actioning segments with an acceptable level of statistical validity, media planners may forego some of the statistical rigor (relax confidence levels from 95% to 90% or even 85%) in order to consider the segments from a more practical and actionable perspective.

The three macrosegments complement the traditional metrics (expenditure per person, length of stay, number of trips, etc.) generally used to assess international tourists as a single market. However, it is possible to use the same metrics on a segmented basis as applied to the total market in order to further enhance the profiles of the macrosegments. For instance, the duration of stay and number of visits to Cape Town over the past five years indicated the following for each of the macrosegments: The shortest length of stay is achieved by tourists of the pleasure seekers segment, while tourists of the vibrant and energetic segment have the longest length of stay in Cape Town. The length of stay for tourists of the established and settled segment is longer than the pleasure seekers, but shorter than the vibrant and energetic segment. The established and settled and vibrant and energetic segments also tend to visit Cape Town more often than the pleasure seekers segment. Ultimately, market strategists and media planners have to be satisfied that the macrosegments selected for targeting are homogeneous (a lot alike within segments) and heterogeneous (a lot different between the segments).

Cape Metro Tourism could also consider several key distinguishing attributes among the segments for use by media planners during the development of different marketing messages. An indication is provided in the research of those attributes which suggest statistically significantly differences among the macrosegments. The findings of the research suggest that cultural aspects with specific reference to Cape Town as a cosmopolitan city, the diversity of cultures, the variety of arts and crafts, and the many cultures found in one city vary statistically when different combinations of macrosegments are considered. In terms of demographic variables, the age of the tourist, occupation, and family lifecycle are attributes which may be considered when developing a message targeted at one or more of the macrosegments.

By also focusing only on the country of origin, the sensitivity analysis suggests that family lifecycle, together with the diversity of cultures and the cosmopolitan nature of Cape Town, are important market delineators for tourists from the United Kingdom and Germany for all three segments, while the United States features strongly as a country of origin among tourists from the vibrant and energetic segment.

The predictive ability of the artificial neural networks discussed in this paper could also assist Cape Metro Tourism to identify potentially new and/or profitable international segments from surveys conducted in the future. This would be achieved by developing a model from a combination of ''high'' and ''low'' value tourists. Those that partake in follow-up surveys would then be classified as ''high'' or ''low'' value based on the same combination of key variables. Segment profiles could be compiled on the basis of knowledge obtained from the introduction of new survey data to the model. Cape Metro Tourism may want to increase the number of tourists to the destination by targeting international tourists who visit other countries but display a similar profile of those who visit Cape Town. A survey of those who visit the destination and those who do not could be useful for determining profiles for each group and matching the profiles in order to obtain an indication of those who could be targeted as potential tourists to Cape Town. This type of information would be useful and could be applied effectively when developing campaigns for targeting tourist segments within specific origin countries.

CONCLUSION

The research findings suggest that the methodology and application of a SOM neural network is useful for segmenting the international tourist market of Cape Town. Furthermore, using a BP neural network model also provides additional market knowledge and, together with the SOM approach for segmenting the tourist market, may improve Cape Metro Tourism's understanding of the international market. Currently, the organization only conducts descriptive analysis of the research data collated from international tourists and undertakes no modeling of the nature and scope described in this paper. Due to the predictive nature of neural networks, Cape Metro Tourism has an opportunity to use the surveys conducted on a continuous basis to track and understand changes in the behavior and profiles of tourists within and between the macrosegments over time.

The deployment of the neural network models appears to have merit, even if the intention is only to use the technology as a basis to enhance the market strategists' and media planners' understanding of changing behavior among tourists within and between the macrosegments. If this were the rationale for deployment of the neural networks, various microsegments could be identified with an opportunity to disaggregate data and develop macrosegments. The use of the segmentation model will assist to achieve these analytical objectives.

The introduction of alternative assessment tools—such as predictive techniques and the ability to assess patterns through the interaction of variables and not independently—also offers Cape Metro Tourism an opportunity to expand their research horizon: by focusing on the discovery of new profitable tourist segments and by identifying international tourists who do not visit Cape Town, but have a similar profile of the tourists frequenting it. A

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