Strategic Segmentation: The Art and Science of Analytic Finesse

Introduction

This chapter brief describes two use cases for strategic analytics that involved segmentation methods used for strategic analytics. One use case was for a product marketing analysis and the other was used for a sales segmentation focus. These two examples were real business situations where product and sales executives needed guidance and direction that was based on data. In both cases, however, the original mindset from the business had some preconceived ideas as how to approach and recommend certain attributes based on their historical knowledge of the available data. In both cases the historical data had changed and therefore the data-driven approach that I took changed the course of the analytics due to the nature of the preconceived ideas. This is where data and business domain expertise must work hand-in-hand in order to achieve the desired goals and objectives needed by each of these organizational groups.

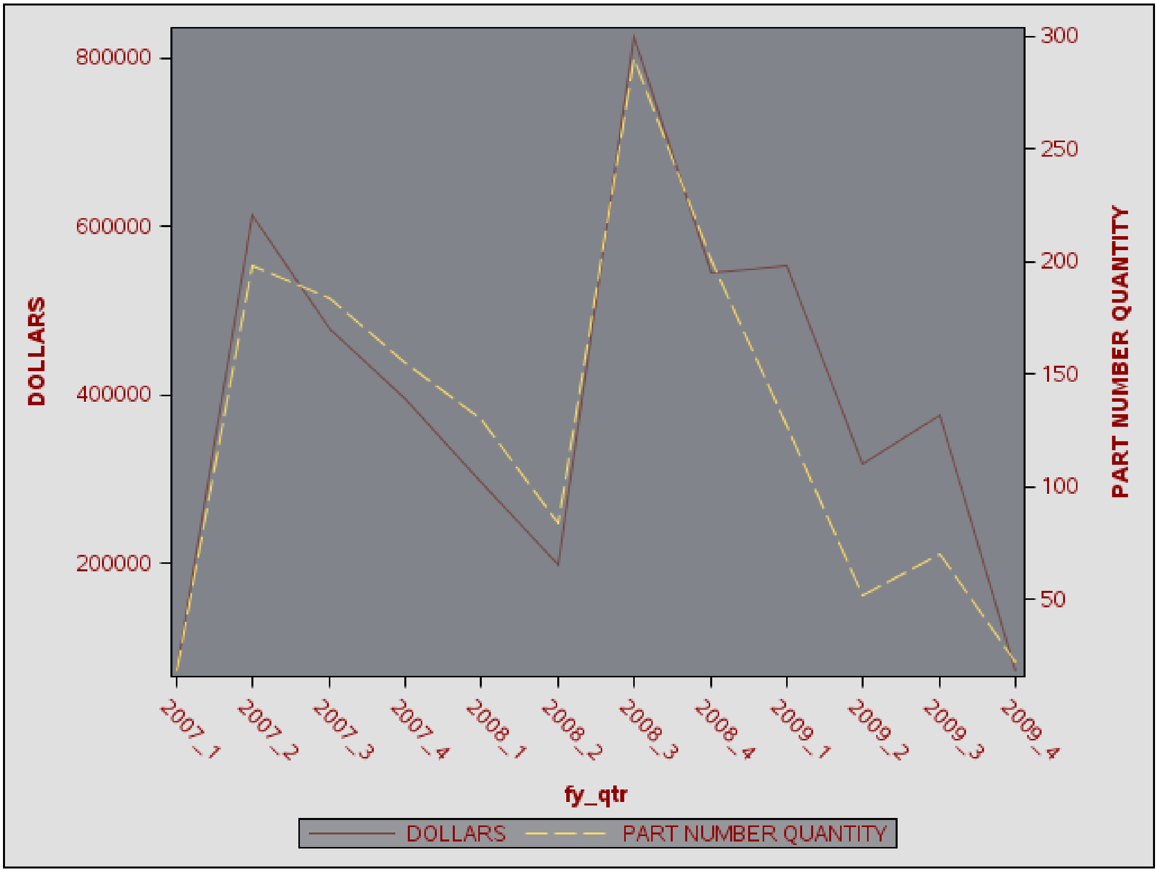
The analytics methods used in this chapter brief are almost identical to the methods used in more tactical segmentations [1]. The differences between strategic versus tactical segmentation typically lies in the data elements used to define the segmentation and how one will use and act upon the results. It is my hope that these two use case examples will help you in your endeavors to make the most out of your organization's data and to do so ahead of what your competition may already be doing. It is in the spirit of mutual cooperation between data mining analysts, business domain experts, and management that the results of the analytics truly become extremely valuable to an organization. It is when the organization then acts upon the results does the analytics take on value and set the course of change for the better according to its goals and objectives.

Use Case 1: Strategic Product Segmentation

It was late in 2009 when a senior product manager came to me and asked for my assistance in a project that required setting the course for new directions for this product line of the business. At this time period in the high-tech industry, changes in computer technology were migrating to more commodity based hardware and data centers around the US and the world were taking note and making changes in their purchasing decisions and plans for how data centers operate. Because of this apparent change in direction, the senior management needed some data driven insights to assist them in what course of action to take in the future.

The senior product line manager had told me that there were four accounts that he believed I should focus as my “target” purchasing trend behavior and should fashion the strategic analytics thereof. I then immediately proceeded to extract the historical data for these four customer accounts to review these trends. What I discovered was the trend that the product line manager thought was a “good” trend turned out not to be quite what he expected. In fact, the trend was quite the opposite of his initial expectation – it was heading downward not upward! Figure 1.1 on page 3 shows the average of the four account trends (names left off for proprietary reasons). As you can observe these trends were not exactly what was expected. Although the volume in revenues and quantities were reasonably high, the trend certainly wasn’t what we desired to set the pace for in the future. At this point of the analysis, I had a serious decision to make as to how to approach the strategic segmentation project.

Figure 1.1 *Four Account Trends Averaged*



The basic question I had to answer was if I was going to use the data as originally planned as the "target" trend in which to measure all other accounts on and therefore segment the customer base with, or was I going to use something different? I thought about this dilemma for a bit and came to the conclusion that this would be a great learning moment for data driven methods. I decided to keep that trend, however, I would look for other trends that were better suited for the goals and objectives of the product line. They chose these particular accounts because they thought the trend was at least flat or heading upward based on their past experience with these strategic accounts. Indeed, the trend downward wasn't going to be helpful for this analysis. I set out to find accounts that exhibited a more positive trend even though their level of revenue and quantity isn't quite near the level of these accounts. My rationale was the right trend was more important to this project than the current volume.

The steps I used in the data prep and analytics are outlined in Table 1.1 on page 4.

Table 1.1 Steps Used to Prepare Data for Strategic Product

Step	Process Step Description	Brief Rationale
1	Selected product lines needed in the products data table.	Query only product lines needed in this analysis.
2	Using the product line codes from previous query, I then queried the product purchase transactions between dates of 2007 and end of 2009.	Queried product transactions purchased in dates of interest.
3	I then aggregated the total revenues and quantities by purchase channel (direct, indirect) by customer account.	Aggregated customer transactions.
4	I then queried the transactions for the four accounts the product manager desired. I also selected a few targeted accounts that had the product line transactions with increasing purchases over time.	Better product purchase transactions for a ”target” group to measure against.
5	I labeled the accounts with the target transactions as well as the four originally selected by the product manager.	Account labeling accomplished by using a SAS format for unique account ID’s.
6	With customer pruchase tansactions labeled by account ID in step 5, I ran a transaction similarity measurement [2] that measured the distance between the ”target” accounts and all others.	Meauring the average distance from all product transactions to desired ”target” group.
7	Merged the average transaction similarity metric along with the the labeled accounts with the customer firmagraphic data and market share estimates using predictive models previously developed.	Final merge of data sets.

Step	Process Step Description	Brief Rationale
8	Performed clustering on the final data set and noted variables that impacted the segmentation and profiled the segments.	Profiled cluster segmentation.
9	Generated charts and diagrams and gave presentation to senior product line managers with recommendations for next steps and direction.	Final analytic insights and recommendations.

The process in step 7 measures a target transaction to all other transaction in both the magnitude and time unit dimensions [2]. The procedure gives a distance metric which when clustered together gives transactions of similar shape in magnitude (quantity of purchase) and in time. This in effect performed transaction clustering along with customer clustering based on other firmagraphic information such as market share, industry group, etc. All the data prep and queries were done using base SAS code in SAS Enterprise Guide. The similarity metric used the similarity procedure (a SAS/ETS procedure) and the cluster segmentation was done in SAS Enterprise Miner.

The clustering results produced a segmentation of 10 segments, of which 3 were considered as high-priority for future growth potential for the product directions. The variables that made an impact in this segmentation were first chosen as potential candidates based on my analyst’s knowledge of the data which I was very familiar with, and the estimated market share potential which I also developed analytic predictive models previously [3]. Table 1.2 on page 5 and Figure 1.2 on page 6 show a table and chart, respectively, of the variables that influenced the 10 clusters and their profiles.

Table 1.2 *Key Variables Affecting Strategic Cluster Segmentation*

Variable	Relative Importance
Company Segment	1.000
Industry Group	0.909
Log (ISS TAM)	0.780
RFM	0.778
Log (Similarity)	0.673

Variable	Relative Importance
Log (Yrs Purch)	0.528
Orig Segment	0.321

Figure 1.2 *Key Variables Affecting Strategic Cluster Segmentation*

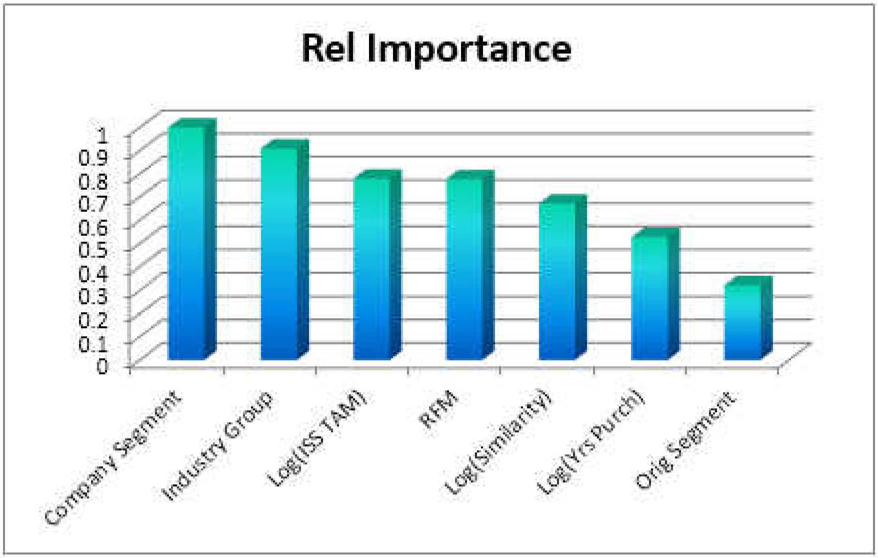


Table 1.2 on page 5 shows that the Company Segment is the largest contributor but the variable that indicated the product line manager's original segment based on his historical knowledge was the least important. The Company Segment was derived from their company's account reference file which indicated if the account was a corporate account, an enterprise or commercial account, or SMB, based on their definition that was applied as business rules and was adhered to for all countries. Of primary importance in this was the industry that the company was in and the estimate of the estimated market called TAM or total addressable market. RFM is a typical Recency, Frequency, and Monetary value segment described Chapter 4 of [1]. Once you have the estimated TAM at the customer account level, the estimates and other key attributes can be aggregated easily. The similarity metric also played an important factor as well. Figure 1.3 on page 7 shows the value of the TAM per capita (total TAM divided by number of customers per segment) for the ISS product line group. Cluster segments 6-8 are considered the most valuable. Figure 1.4 on page 8 shows the aggregate general relationship between the average similarity metric, ISS TAM, and the average number of years of customer purchase. This shows that there were non-linear relationships among these variables and the cluster segmentation did take this into account in the final clustering analysis. So the segments which show the highest average similarity and number of years purchase, also had the highest average TAM.

Figure 1.3 Total Addressable Market Estimates by Strategic Cluster Segment

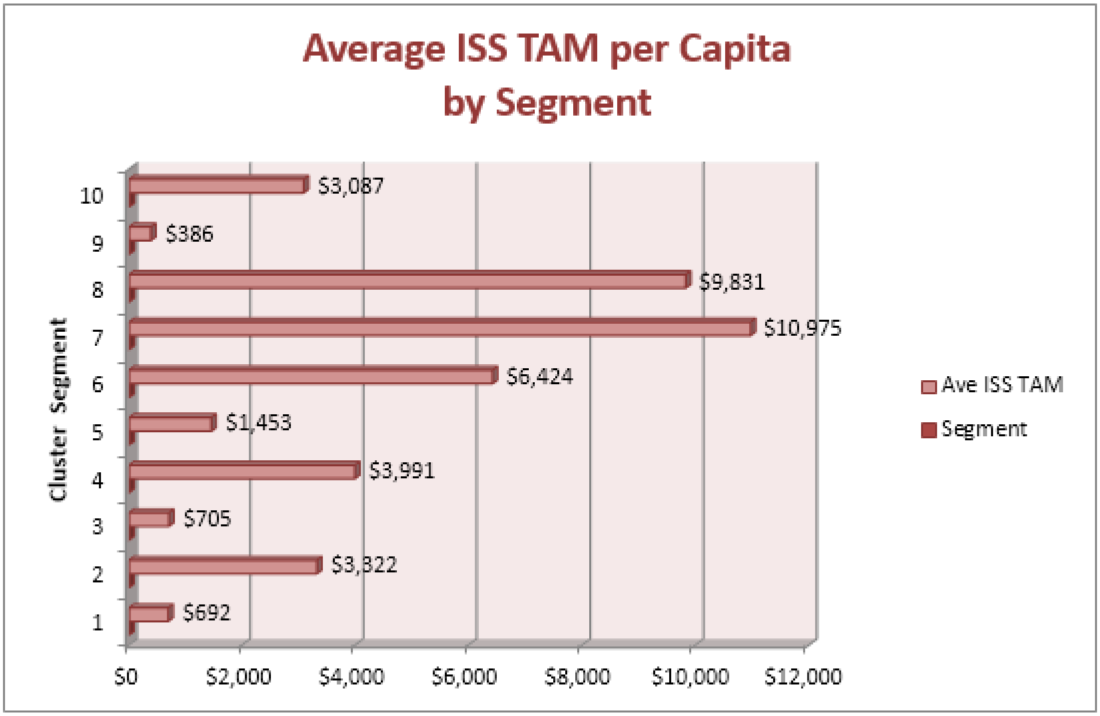
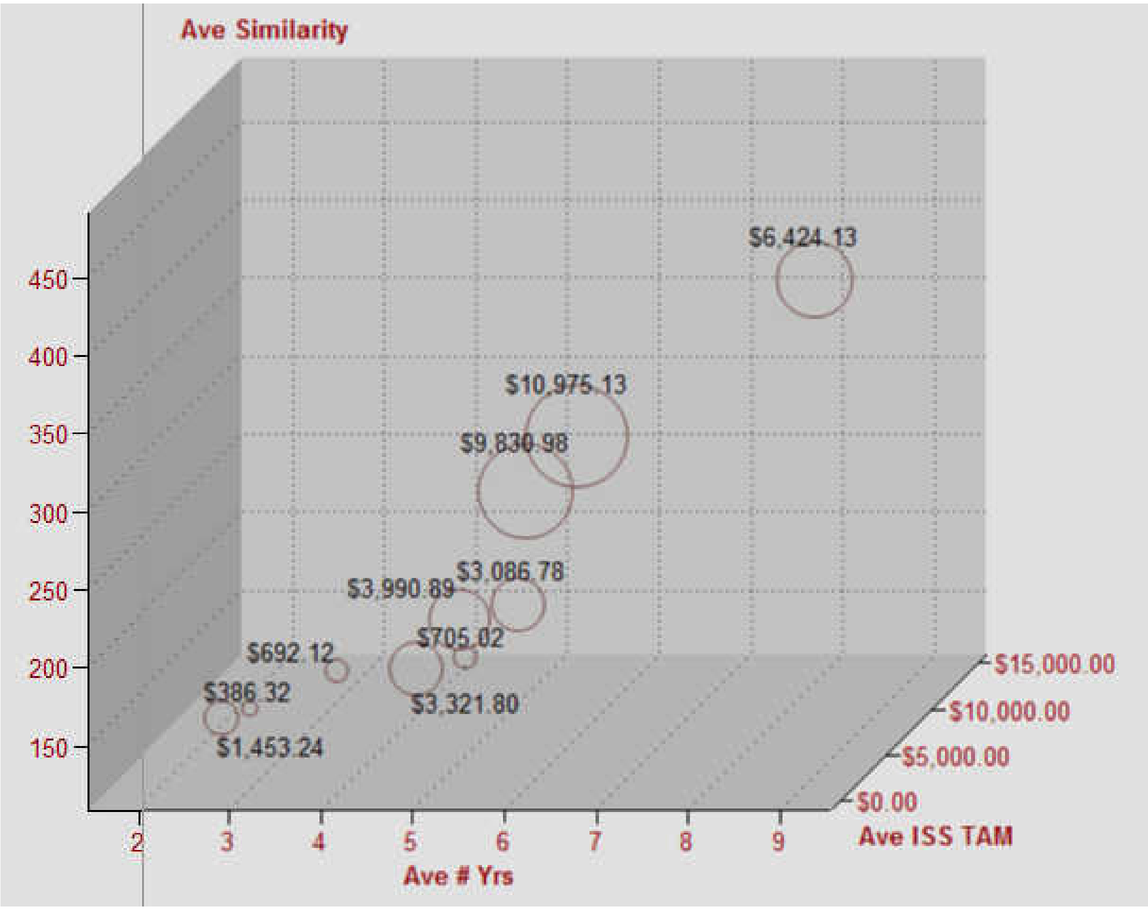


Figure 1.4 *Plot Showing General Relations Ave ISS TAM, Similarity, Yrs. Purchase*



The product line management team was impressed by using such advanced analytical methods such as clustering of transactions into similar groups and using market share estimates as well. The also were aligned on the insights from the cluster segments that where of high-value and allowed more strategic plans to be developed. Again, what differentiated this from a tactical segmentation was the fact that I used semi-supervised techniques. Although clustering is an unsupervised method, I gave it some general direction by using variables such as a metric that measured how close the target transaction shape to all other transaction shapes and also an estimate of the market share. This market estimate was developed by me almost 11 years earlier using SAS Enterprise Miner with a two-stage model [3]. The product line management using the 3 high-value clusters and others that were more mediocre clusters was able to make definite strategic plans for customer accounts and target them much better by what industry and size they were, etc. So the elements one places into the segmentation will strongly influence if the segmentation can be used strategically or not.

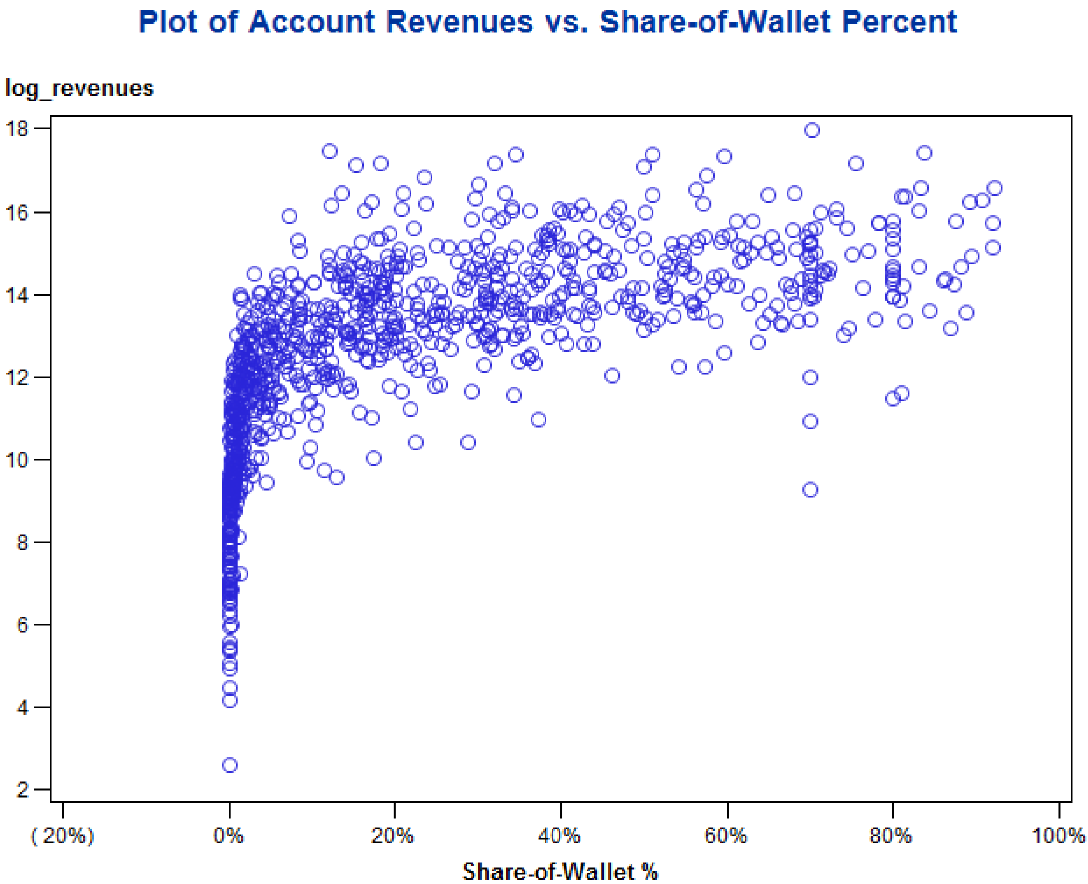
Use Case 2: Strategic Sales Segmentation

This use case came out of a project where a contractor who showed me this unique way of segmenting sales accounts. The key and trick to this is similar to the use case 1 in that it requires an estimate of the revenue (or profit) share-of-wallet estimate in each account. When you are able to estimate the amount of total spending that the account can spend relating to the products and/or services you organization can supply, then the revenues you do generate from that account divided by the total spending estimate becomes the estimated share-of-wallet or SOW. This can be a very powerful metric to have if the estimate is reasonably accurate. Sales can use these estimates for strategic planning in areas such as:

- quota setting,
- account prioritization,
- product and messaging approaches,

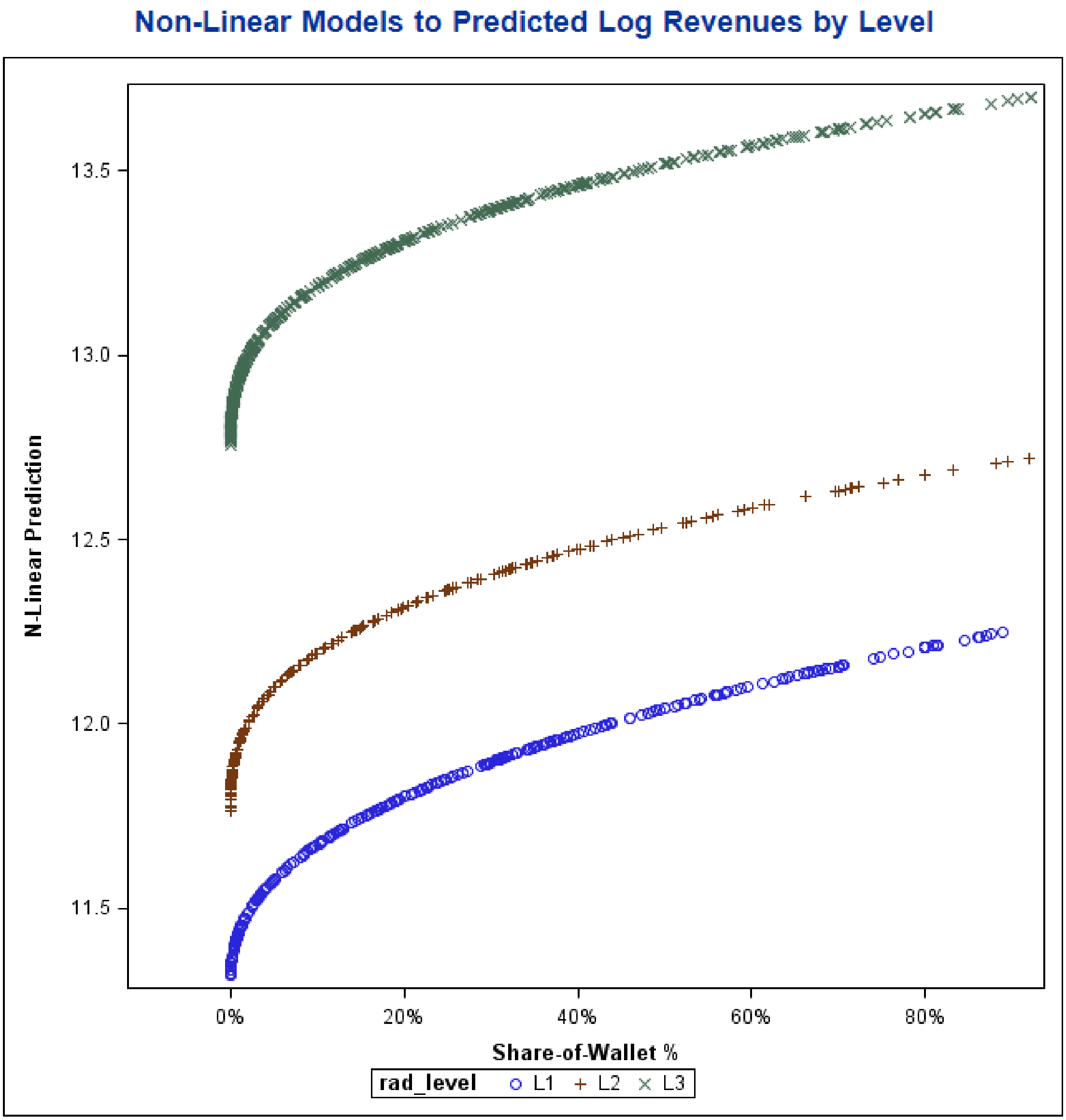
and other areas as well. The business needed to segment the accounts so that their planning and goal setting process could be enhanced using the data driven methodology at understanding the potential versus their actual spending for IT products and services. Again, the models that were developed in [3] were used in this particular Business Unit and the planning process needed this segmentation and estimates at the account level, not just the total spending by industry like one obtains from syndicated reports. The plot in Figure 1.5 on page 10 shows about 1,000 accounts with the Log of their latest year's revenues vs. the estimated Share-of-Wallet (SOW) percent. What this plot shows is the non-linear relationship between these metrics, however, it is very difficult to see any other particular pattern. One of the objectives that the sales management needed to accomplish by segmenting the sales accounts was to assist them in their sales planning and operations for the upcoming year. Historical segmentation methods relied heavily on a corporate segmentation based on revenues the business sold to their customers and the major industry of the account. Segmenting the accounts in Figure 1.5 on page 10 with historical corporate segmentation methods didn't produce any usable analysis. So, the segmentation proposed is to carve out some delineation of revenue and the SOW so that they could start the planning process. The segmentation in this case carved the SOW percent into three groups with splits at 10% and 40%. For the revenues, the two splits were $125k and $350k. This produced nine segments. Now, when you fit a non-linear model to the three different SOW levels, one obtains the plot shown in Figure 1.6 on page 11.

Figure 1.5 *Account Revenues and SOW Percent*



Now, in Figure 1.6 on page 11 one more clearly observes the relationship for the differing SOW segments. Each of the nine segments had a sales strategy that fit their SOW level and the total revenues that could be expected. Using other models in tactical campaigns, one could better offer certain cross-up sell products or services that better fit according to the expectations. The levels of R, A, and D represent Retain, Acquisition, and Develop. This strategy was used successfully in several of the major business units. This segmentation was also combined with other segmentations around the organization to improve the efficacy of marketing and potentially in market research.

Figure 1.6 *Non-Linear Model Fit by Segment Level*



While the above two business use cases were simple in nature, the models used to create the needed estimates at the account level were not very simple.

References and Further Reading

[1] Collica, Randall S., *Customer Segmentation Using SAS™ Enterprise Miner, 2nd ed.*, SAS Institute Press, 2011.

[2] Chapter 24 Similarity Procedure, *SAS/ETS ™ 13.2 User Guide*, SAS Institute Inc, 2014, Cary, NC., USA.

[3] Collica, Randy, *Estimating Potential IT Demand from Top to Bottom*, SAS Global Forum paper no. 371, Seattle, WA., 2010.