Strategic Segmentation: The Art and Science of Analytic Finesse

Introduction

This chapter briefly 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 are from real business situations where product and sales executives needed guidance and direction that was based on data. In both cases, however, the businesses 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 that were originally based on those 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.

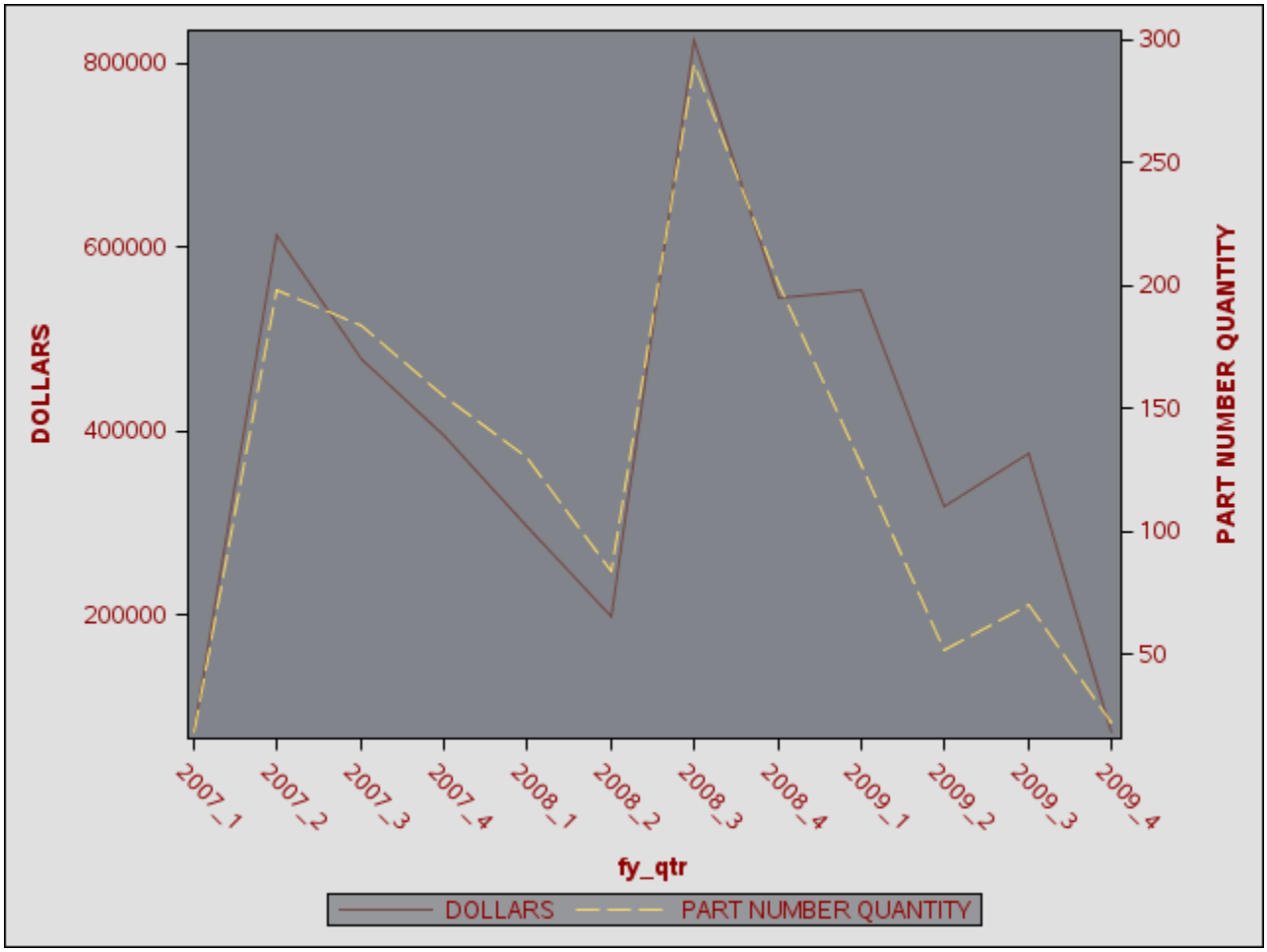
The analytics methods used in this chapter are almost identical to the methods used in more tactical segmentations [1]. The differences between strategic versus tactical segmentation typically lie in the data elements used to define the segmentation and how you use and act upon the results. It is my 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 among data mining analysts, business domain experts, and management that the results of the analytics truly become valuable to an organization. It is when the organization then acts upon the results that the analytics take on value and change the course for the better according to its goals and objectives.

Use Case 1: Strategic Product Segmentation

Late in 2009, a senior product line manager came to me and asked for my assistance in a project that required re-setting the course for this product line. At this time 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 choosing a course of action to take in the future.

The senior manager had told me that there were four accounts that he believed I should focus on as my "target" purchasing trend behavior and should fashion the strategic analytics accordingly. I immediately proceeded to extract the historical data for these four customer accounts to review the trends. However, the trend that the product line manager thought was a "good" trend turned out not quite what he expected. In fact, the trend was the opposite of his initial expectation–it was heading downward not upward! Figure (1) shows the average of the four account trends (names omitted for proprietary reasons). As you can observe, these trends were not exactly what was expected. Although the volume in revenues and quantities was 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 - Four Account Trends Averaged



The basic questions were should I use the data as originally planned as the "target" trend with which to measure all other accounts and therefore segment the customer base, or should I 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 the "target" trend. However, I would look for other trends that were

better suited for the goals and objectives of the product line. The company chose these particular accounts because they thought the trend was at least flat or heading upward based on their 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 wasn't quite near the level of these accounts. My rationale was that 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) below.

Table 1 - Steps Used to Prepare Data for Strategic Product Segmentation

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 2007 and end of 2009.	Queried product transactions purchased on dates of interest.
3	I then aggregated the total revenues and quantities by purchase channel (direct or indirect) by customer account.	Aggregated customer transactions.
4	I then queried the transactions for the four accounts that 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	Account labeling accomplished by using a

Step	Process Step Description	Brief Rationale
	well as the four originally selected by the product manager.	SAS format for unique account IDs.
6	With customer purchase transactions 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.	Measuring the average distance from all product transactions to desired "target" group.
7	Merged the average transaction similarity metric along with the labeled accounts with the customer firmographic data and market share estimates using predictive models previously developed.	Final merge of data sets.
8	Performed clustering on the final data set and noted variables that affected 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 against all other transactions in both the magnitude and time unit dimensions [2]. The procedure gives a distance metric that 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 firmographic information such as market share, industry group, and so on. 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 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 for which I previously developed analytic predictive models [3]. Table (2)_and Figure (2) show a table and chart, respectively, of the variables that influenced the 10 clusters and their profiles.

Table 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
Log (Yrs Purch)	0.528
Orig Segment	0.321

Figure 2 - Key Variables Affecting Strategic Cluster Segmentation

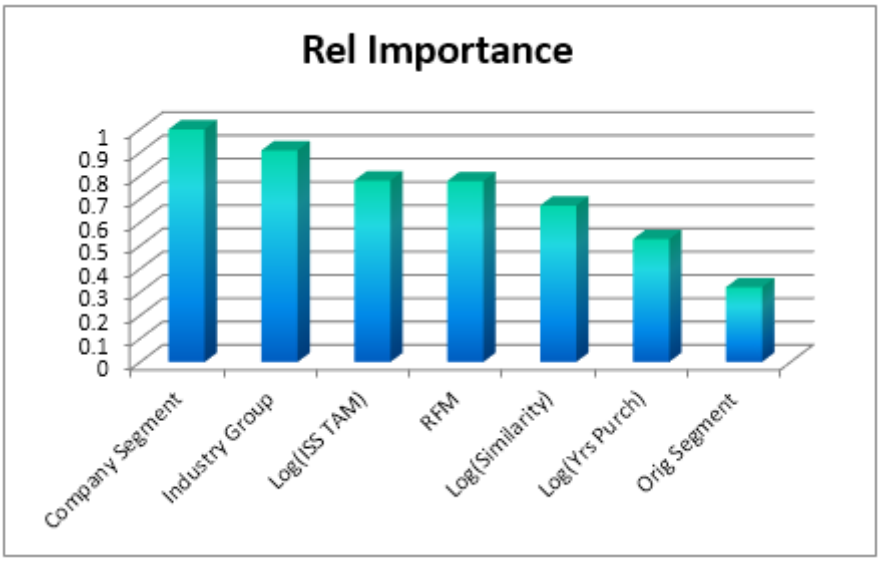


Figure (2) shows that the Company Segment is the largest contributor but the variable called Original Segment based on the manager's historical knowledge was the least important. The Company Segment was derived from the company's account reference file, which indicated whether the account was a corporate account, an enterprise or commercial account, or SMB, based on the definition that was applied as business rules and was complied with by all countries. Of primary importance in this was the industry that the company was in and the estimated market called TAM or total addressable market. RFM is a typical Recency, Frequency, and Monetary value segment described in 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. Figure (3) 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 (4) 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. The cluster segmentation did take this into account in the final clustering analysis. So the segments that show the highest average similarity and number of years purchase also had the highest average TAM.

Figure 3 - Total Addressable Market Estimates by Strategic Cluster Segment

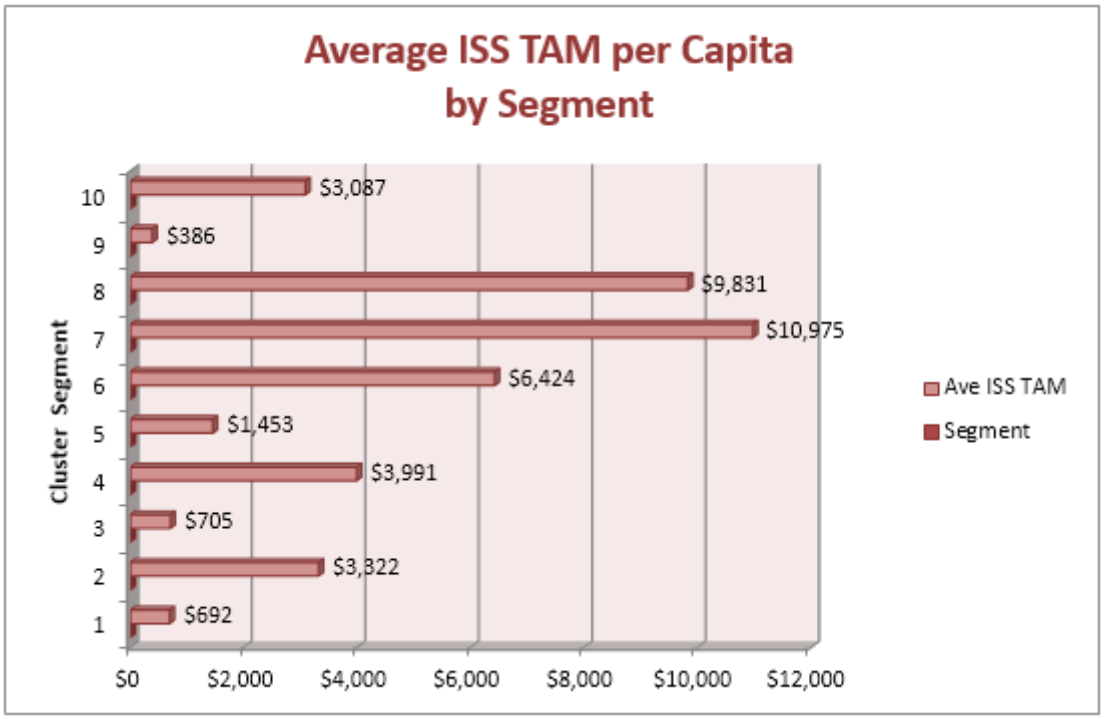
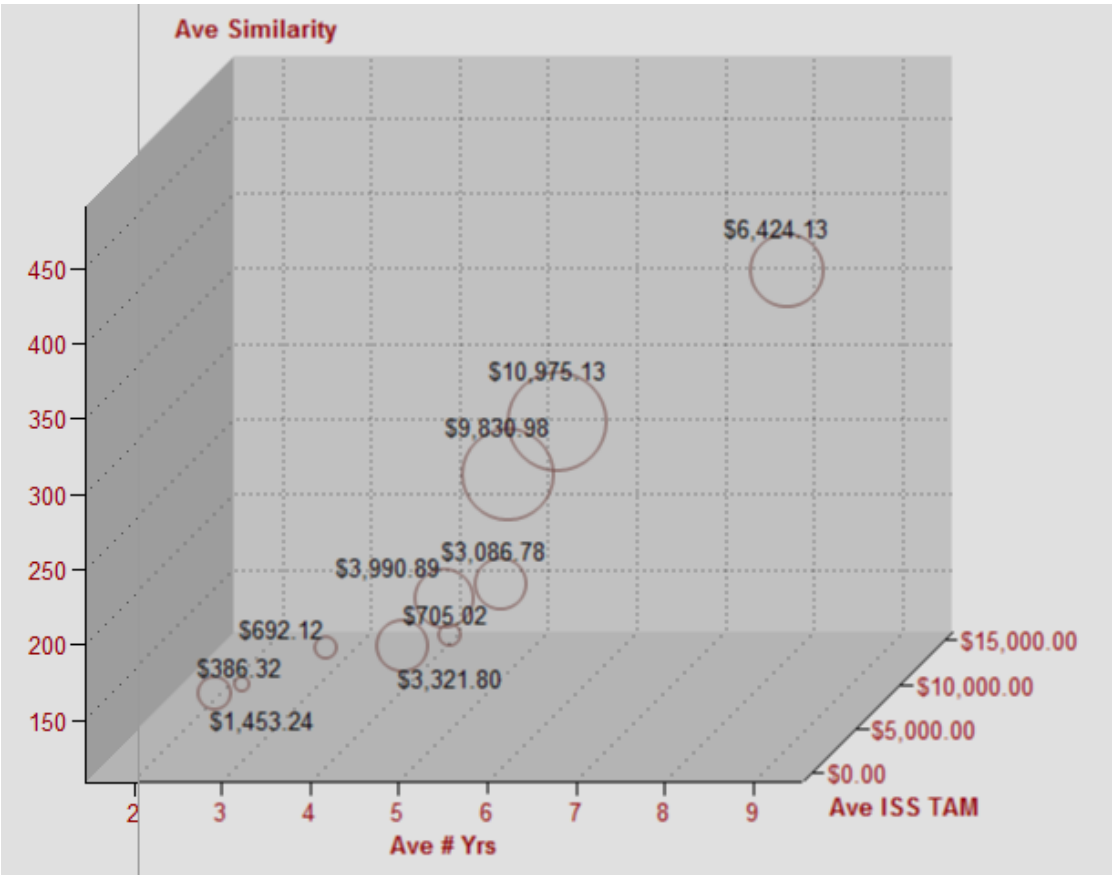


Figure 4 - Plot Showing General Relations Ave ISS TAM, Similarity, Yrs. Purchase



The product-line management team was impressed by advanced analytical methods such as clustering of transactions into similar groups and using market share estimates. They 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 was 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 other more mediocre clusters was able to make definite strategic plans for customer accounts and target them much better according to industry and size, and so on. So the elements that you place into the segmentation will strongly influence whether the segmentation can be used strategically.

Use Case 2: Strategic Sales Segmentation

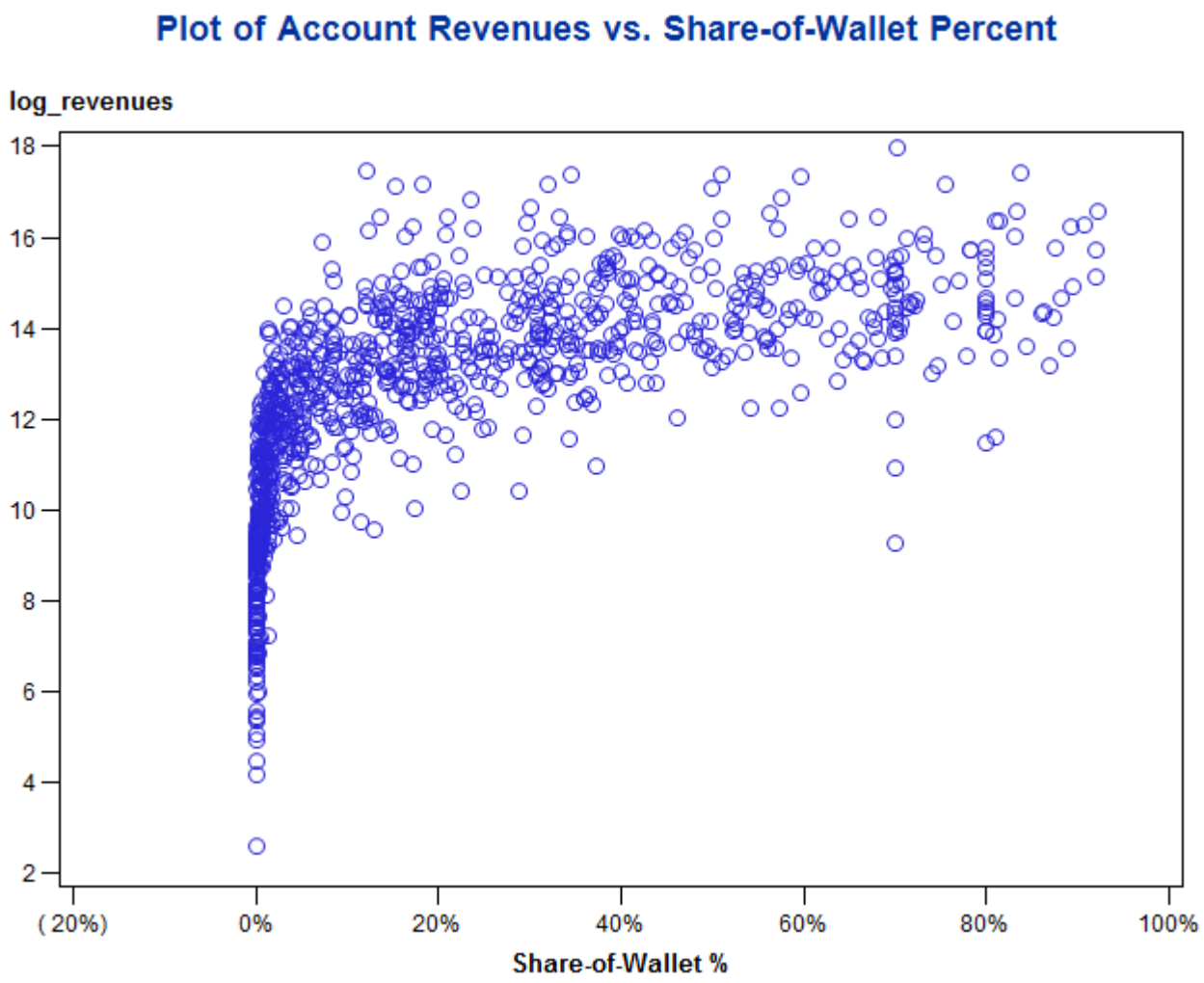
This use case is from a project where a contractor showed me this unique way of segmenting sales accounts. The key to this method is similar to use case 1 in that it requires an estimate of the revenue (or profit) share-of-wallet estimate in each account. When you can estimate the amount of total spending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

- quota setting
- account prioritization
- product and messaging approaches

The business needed to segment the accounts so that their planning and goal setting process could be enhanced using the data-driven methodology to understand 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 you can obtain from syndicated reports. The plot in Figure (5) shows about 1,000 accounts with the Log of their latest year's revenues versus the estimated Share-of-Wallet (SOW) percent. What this plot shows is the nonlinear 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 historical revenues rather than current behavioral characteristics. Segmenting the accounts in Figure (5) 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 $125,000 and $350,000. This produced nine segments. Now, when you fit a nonlinear model to the three different SOW levels, you obtains the plot shown in Figure (6).

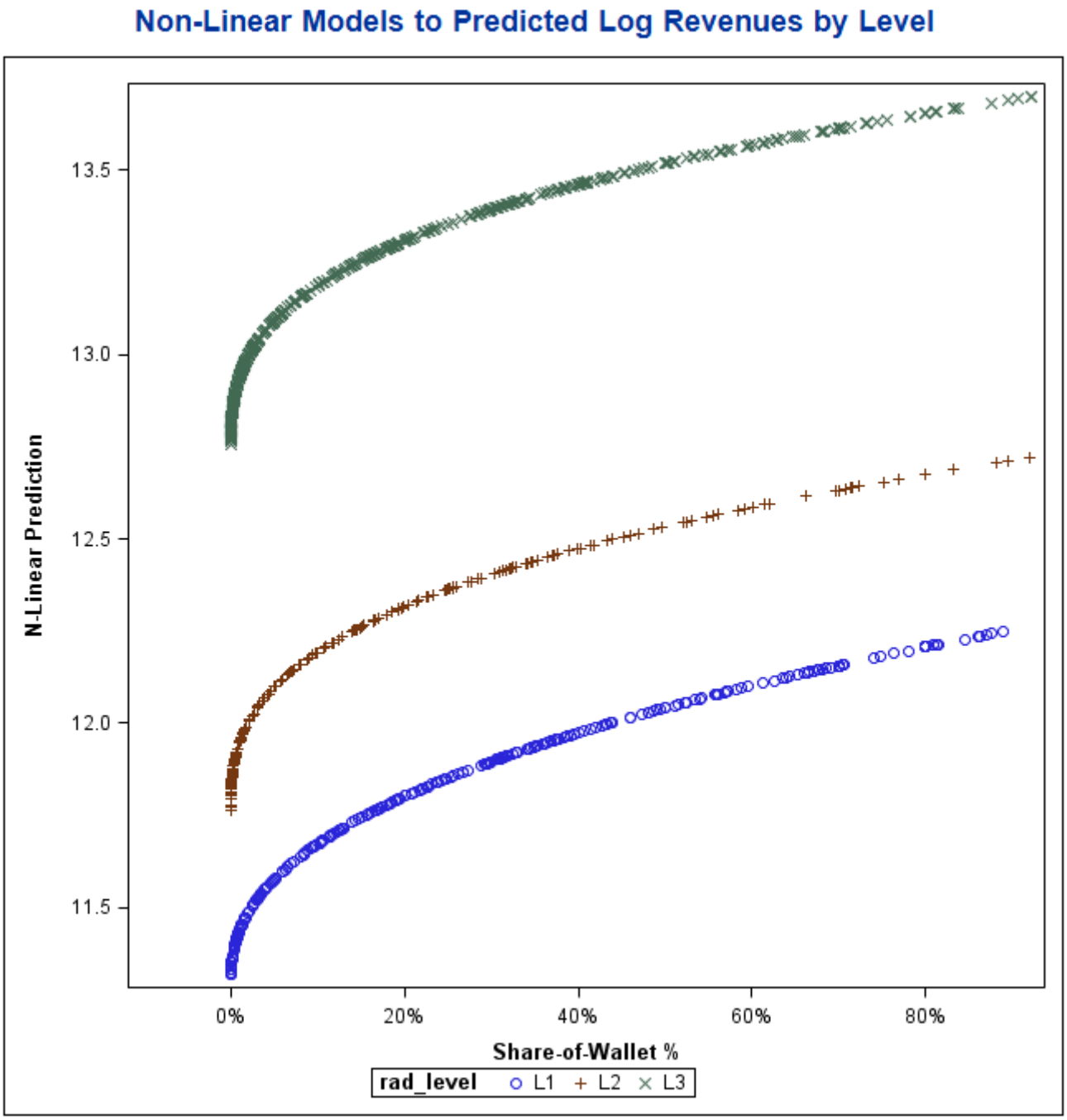
Figure 5 - Account Revenues and SOW Percent



In Figure (6), you can more clearly observe the relationship for the different 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, you could 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 6 - Non-Linear Model Fit by Segment Level



The above two business use cases were simple in nature, but 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 Inc., 2011.

[2] Chapter 24, Similarity Procedure, *SAS/ETS 13.2 User's 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.