From Customer Risk to Corporate Strategy:
Using Text Analysis and Predictive Modeling to Improve Promoter Scores
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Overview

The idea of evaluating customers for the monetary risk they pose to a business is not a new concept. However, the idea of trying to understand customers’ future monetary values – and the probability of their future risk – is perhaps rather new. Most corporate risk assessments center on company risk, such as how much liquid capital the company has, how much debt it carries, or the risks to business operations or facilities, etc. When you appraise a set of company assets, only a few things show up that really matter:

- Customers and their continued patronage.
- Employees and their knowledge (as well as their work productivity).

These two assets greatly influence the success or failure of a company. With that in mind, this paper focuses on how to evaluate the likelihood of continued customer patronage versus the risk of losing it. It also acknowledges corresponding loyalty, measured in the form of promoter scores.

What Are Promoter Scores?

The notion that a customer may or may not continue to purchase, subscribe, renew, etc., relates to whether he has increased or decreased his spending. It's also possible to measure customer risk by surveying a customer’s intentions to promote your brand, your product or your service. Often, these types of surveys are handled by the organization itself, but third parties sometimes conduct the surveys instead. Surveys are conducted on a sample set of customers. Once complete, the survey responses are typically merged with the customer data on which the sample was based.

A promoter score is a metric that indicates how likely a customer is to recommend a product or service. So, a survey might ask: How likely are you to recommend Product X to a colleague? By selecting a value from 1 to 10, companies obtain a promoter score. Often, these scores are ranked by being placed into one of three levels: promoter, neutral or detractor. Figure 1 shows a typical categorization scheme.

While surveying customers provides valuable insight into the opinions of those surveyed, it is not practical to survey every customer. The question arises: How do you more broadly apply the insights derived from your customer survey data? Many organizations develop reports based on survey responses. But the true value of surveys is derived only if you can do something more with the results. In many cases, managers are unable to use customer insights obtained through surveys to help them make more strategic business decisions.
Using Text to Predict Promoter Scores

For ongoing financial success, organizations must have a very clear and effective growth strategy that can be well executed and enhanced over time. Many factors can influence long-term sustainable growth and financial performance. But the factors that affect how customers perceive the goods and services they purchase are vitally important to understand. Many organizations embrace the concept of customer loyalty, but just as many struggle to find an easy way to quantify the monetary impact and decisions associated with improving customer loyalty metrics.

To quantify the impacts to the entire customer population, organizations can extend their survey results by using the promoter scores to predict the behavior of customers who were not surveyed. One method of doing this is to gather all of the customer contact history and combine this unstructured text with the survey promoter score responses – as well as with the structured data the organization already has. Unstructured text can include verbatim comments from the promoter survey, call center notes, and comments from sales or technical support representatives.

It is extremely informative to analyze these combined text data sources. As demonstrated in this paper, the analysis can successfully predict promoter scores. Moreover, by combining the scores with customer revenues and other financial metrics, you can examine the relationship of the likelihood to be a promoter (or detractor) with your potential revenues. Then you can use this relationship to develop strategic plans centered on the voice-of-the-customer (VoC). For example: If X number of customers are moved from passive to promoter status, what is the effect on overall revenue?

This paper illustrates a methodology that organizations can use to develop reasonably accurate models from call or support center notes (obtained from ongoing customer communications). When mined, these notes can be used to predict the likelihood to recommend for the entire customer base, including people who were not surveyed. Once this scoring process is complete, an aggregate of these predicted scores are used along with financial metrics to create econometric models. These models simulate the overall relationship between the likelihood of being a promoter – and customer net revenue, customer lifetime value and other financial metrics.

Quantifying Customer Promoter Scores as a Risk Metric

Risk is a relative concept. What is considered risky from one point of view may not be considered risky from other perspectives. So what is customer risk? To answer this question, we need to define risk with respect to some sort of measured quantity. For example, consider revenue growth from customer purchases. Finance departments often compute revenue growth as a compound annual growth rate (CAGR) or year-over-year growth (YOY). While these metrics are useful, they do not help organizations forecast growth or assess the likelihood that customers will continue to purchase in the future. Forecasting is much more complicated than a simple formula can reflect. Fortunately, there are well-defined methods that allow us to estimate future growth based on whether or not growth occurred previously.
If a customer makes purchases for a specific time period (say, five years) – and if the year-over-year growth is 0 or negative – we classify this customer as being at risk for negative revenue growth. Other metrics, such as units or quantities, can be categorized in this fashion as well. The reason we quantify the revenue or quantities of purchases is to frame the problem of a specific behavior (negative revenue or unit growth, for example) into two distinct categories: 0 and 1. If the customer is classified as a 1, then her past behavior indicates negative growth; if she is classified as a 0, then her past behavior is classified as stable or increasing growth. The business problem has now been quantified as having a binary outcome (a 1 or 0), and the likelihood of being a 1 becomes a measure of customer risk. This risk metric can then be forecast into the future by using the historical, known behavior, along with other customer demographics such as tenure, geography, segment, etc. – and by combining this data with the text notes from customer engagements that have been recorded over time. Armed with all this data and the customer risk categorization, we can now develop a predictive model to assess the likelihood of this risk condition and forecast it for future time periods.

You can analyze other customer behaviors, and anything else that is meaningful to the organization, in this same fashion. For example, you can use this methodology to analyze customer newsletter subscriptions, or longevity of the business relationship (churn). If you analyze many customers in this fashion, you can aggregate the future estimates of the growth probabilities by computing their average value or perhaps by aggregating them as a range of values. These individual customer estimates and aggregates can be considered customer risk scores, since the risk of a certain behavior is being modeled over time and forecast for the future. The value of promoter scores is that they help you understand the business impact of creating greater customer loyalty and satisfaction. The value of using unstructured text is that it enables better predictions from promoter scores and provides the reasons why customers are or are not likely to promote your business.

Turning Survey Promoter Scores into an Analytic Model

Now, let’s turn our attention to the general methodology that can translate unstructured text notes into promoter scores. Many businesses struggle to find an easy way to measure customer loyalty or satisfaction and link it to meaningful financial outcomes. This inability to quantify the financial value of customer satisfaction or loyalty programs can impede efforts to invest in and optimize an organization's customer experience strategy.

Organizations often capture “likelihood-to-recommend metrics” such as promoter scores by conducting customer surveys online or by telephone. While it’s important to report the number of positive, negative or passive customer responses, it’s challenging to quantify the monetary effect of migrating customers to a higher level of the promoter score scale. The following is a practical example of this task.
The Economics of Promoter Scores

Many industries and some service organizations now use promoter scores to focus entirely on customer satisfaction metrics. Through ongoing research and application, the link between promoter scores and financial metrics continues to gain acceptance and credibility. But there are still many skeptics, as well as organizations, that haven’t yet taken advantage of the ad hoc data available from their own customer data stores to accomplish these analyses.

Metrics such as average revenue per unit (ARPU), customer lifetime value (CLTV) or potential customer revenue (estimated amount of customer spending per annum) can be examined using this methodology. By performing simulations on their data using econometric modeling methods, organizations can get direct insights into the value of migrating a customer up the promoter score curve – along with the corresponding financial impact to the business. Figure 2 shows an outline of this methodology.

Figure 2 implies that the information contained in customer call notes, transcripts, and support staff logs or emails is typically helpful in predicting the customer’s sentiment and his likelihood to purchase or recommend. The key is to turn these unstructured notes and comments into something that is structured so that predictive models can be developed and applied to the entire customer population.

For model development purposes, it’s usually sufficient to organize the unstructured data for an appropriate time period, such as three or six months, prior to taking the survey. You can then routinely establish a way to spot-check the survey model. For example, you can select a random sample of customers scored with the model that predicts the likelihood to recommend (or purchase), and then send those same customers the survey and compare the model’s predicted results with the customers’ actual responses.

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If the model used to predict these promoter scores does not automatically generate confidence intervals of the predicted values (such as with a logistic regression), then you can use data simulations to generate confidence estimate bands that surround the predicted values. This set of confidence estimates will give managers a range of values for which the model is expected to predict with a certain level of statistical confidence. This paper outlines the overall process for setting up these modeling processes. It also illustrates how to link the predicted promoter scores to important financial outcomes – such as net operating revenues, CLTV, customer tenure and more.

Analytic Methodology: Data Collection – The Key Enabler for Model Development

Since data is the fuel that analytic models need to run on, data preparation is the necessary foundation for developing and deploying good models. To generate promoter scores, most organizations use surveys to poll customers, clients or prospects about their likelihood to recommend their products or services. Such surveys often collect the data on an ordinal scale – say from 1 to 5 – where 5 is “very likely to recommend” and 1 is “will not recommend.” Other surveys simply ask: “How likely are you to recommend XYZ?” and the possible responses are yes, no or neutral. Still other surveys use a rating scale but allow the respondent to submit open-ended comments. This paper proposes that organizations should combine responses to such surveys with their existing customer data via a customer ID key.

Often, organizations also have data that is unstructured – in the form of notes, memos, emails, Web chats, text messages and social media such as Twitter, Facebook, LinkedIn and the like. This paper focuses on typical structured customer data along with promoter scores, in combination with these unstructured notes that were taken during communications with customers or clients. These notes are often identified by the same set of customer ID keys that already exist in structured customer data repositories.

For analytics to take place, a single row of data per customer must exist that includes fields for both unstructured notes and comments. However, this is complicated by the fact that there may be more than one set of notes and comments per customer, since a customer may have called a customer support person as well as a call center, technical support center and/or customer care center. These comments are typically listed in a set of note transactions taken over a period of time. Figure 3 shows how such unstructured notes may appear.
<table>
<thead>
<tr>
<th>Customer ID</th>
<th>Memo Date</th>
<th>Notes</th>
<th>Note Type</th>
<th>Agent or Sales Rep</th>
<th>Account ID</th>
</tr>
</thead>
<tbody>
<tr>
<td>26432789</td>
<td>5-Nov-2012</td>
<td>Mr. A called to inquire about his account and desired to make a funds transfer. He didn’t know how to do this online and needed assistance. Directions were given to Mr. A, and he is now able to access his account successfully online.</td>
<td>Memo</td>
<td>Mary Jones</td>
<td>E2432J3217</td>
</tr>
<tr>
<td>74382791</td>
<td>6-Nov-2012</td>
<td>Ms. J desired to close her account. She is very unhappy about the service and desired a withdrawal immediately.</td>
<td>Memo</td>
<td>Roger Alpine</td>
<td>A9827K727</td>
</tr>
<tr>
<td>26432789</td>
<td>1-Dec-2012</td>
<td>Mr. A desired to change his portfolio account. Fund A is to be set at 30 percent while Fund B changed to 45 percent. His PIN was also reset as it was locked out as he noted on the call.</td>
<td>Memo</td>
<td>Sally Sander</td>
<td>E2432J3217</td>
</tr>
<tr>
<td>99435673</td>
<td>8-Dec-2012</td>
<td>Sys-Email: Mr. K, this note to you is to confirm your online PIN has been successfully reset. Please click on the link provided below to access your account. Thank you.</td>
<td>System</td>
<td></td>
<td>K9983Q105</td>
</tr>
</tbody>
</table>

**Figure 3: Typical format of unstructured call notes/memo data.**

Notice in Figure 3 that customer ID 26432789 has two entries: One on Nov. 5 and one on Dec. 1. In addition, the last note in Figure 3 is a system-generated note (not entered by an agent). This simple example shows that notes captured over time can be considered transactional unstructured data.

How can you merge this sort of unstructured data with structured customer data that has just one row per customer? One method is to analyze the notes in their transactional form, aggregate the results of the text data, and then merge the aggregated results by each unique customer ID. This method accomplishes two things. First, it captures the transactional form of unstructured data inherently; second, it translates the aggregated results to the customer data fields that also contain the survey results and any other customer fields of interest.

Once this process of data manipulation, aggregation and merging is completed, you can develop a model that predicts the survey responses from the aggregated unstructured data and the structured customer fields.
One final set of analysis remains: applying the predictive survey model to a much larger set of customer data. You can aggregate this model for the estimated survey predictions and for other financial metrics, such as customer lifetime value, net operating revenues, customer tenure and the like. You can also use it in conjunction with econometric methods and strategic what-if simulations that can help an organization answer questions such as:

- What is the financial impact of migrating X number of customers from detractors to promoters?
- What are the key topics that arise when detractors and promoters contact the call center?
- What is the future impact of these survey results?

Answers to questions like these can greatly bolster strategic plans, particularly when they are supported by factual data. Powerful analytic models provide fact-based conclusions with built-in confidence ranges, which give organizations reasonable trust in the estimates. Armed with these insights – and backed by sound methodology, data and analytics – organizations can plan activities with much greater confidence.

**Modeling Development**

Consider a case study from the financial services industry. The data set contains customers from both business-to-business (B2B) and business-to-consumer organizations – however, we will only focus on the B2B side in this paper. The data set includes promoter survey responses matched back to the customer data as well as text fields of notes and memos from customer communications with call center representatives. Some structured data also exists, including customer tenure, estimated customer lifetime value and the like.

The survey asked about the likelihood to recommend the financial service to others. Responses were classified in one of three categories: promoter, neutral or detractor. In the following example, we will determine if both the structured and unstructured data can be used to predict the survey scores and, in particular, the promoter level. If the model is a reasonably good one, then it can be applied to customers with call center note records who did not answer the survey – so the model is used to derive an estimated likelihood-to-recommend score.

Predicting the probability of being a promoter requires having a model that naturally estimates each category level (promoter, detractor or passive/neutral) by a probability ranging from 0 to 1. Algorithms that readily allow this include (but are not limited to) logistic regressions, neural networks and decision trees. To accomplish our goal of predicting the survey response category, however, we must turn the unstructured text into something that an algorithm will recognize as an input. This is where text mining comes in.
SAS® Text Miner parses the call note text using natural language processing (NLP) methods. NLP breaks apart phrases and classifies words into their corresponding language parts, such as nouns, noun groups, verbs, pronouns and the like. This process is called part-of-speech tagging. The software can also perform entity extraction as well as spell checks and word stemming. Entity extraction, for example, means that the software understands that a phrase such as “the White House” is actually referring to a specific place and not just a house that happens to be painted white. The software calculates frequency counts of terms and entities for each document, as well as for all documents in the data set collection. This forms a large but sparse matrix that can algorithmically produce numeric values that are analytically equivalent to the key content of the documents being processed. These numerical values can then be used as input into prediction algorithms to estimate the survey score categories, and thus their estimated probabilities. Figure 4 illustrates a partial output listing of a matrix table of parsed elements from the memo notes in this data set.

![Figure 4: Partial term/phrase document matrix. (Results from NLP text mining.)](image-url)

The data matrix in Figure 4 can now be input for an algorithm that will calculate numerical outputs representing the unstructured textual data. The algorithm performs this task using the attributes and keeping only high information content, while dropping very low information content. The next step is to use this structured data representation of the unstructured text in conjunction with the traditional, structured customer data. In this way, we can predict whether a customer is categorized as detractor, passive or promoter.
To accomplish this task from the matrix in Figure 4, we need to transform the matrix into something that a predictive model such as a regression, neural network, decision tree, etc., can use. This transformation is done using an algorithm called singular value decomposition (SVD). It is beyond the scope of this paper to review the details of how SVD works. However, at a high level, it represents all the unstructured content as nouns, verbs, entities, themes, etc., and places these into 100 or more dimensions of numerical results that are all orthogonal (statistically independent) of one another. These new columns of numeric variables represent the text collection – and predictive models can directly use these variables. To automatically create SVDs from call notes and surveys, you can use the Text Topic node or Text Cluster node in SAS Text Miner.

**Predicting Promoter Scores from Notes and Customer Data**

SAS Text Miner is embedded as an add-on to SAS® Enterprise Miner™, which provides all of the modeling and data mining capabilities you need to analyze your unstructured data and convert it into rich structured data for predictive analysis. You can continue to use these newly created columns in predictive models. Figure 5 illustrates a basic flow for predicting promoter responses.

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After the model is deployed and customer records are scored with promoter score predictions, you can aggregate these scores, along with other customer data of interest. You can then use these aggregated scores to investigate the general relationships between promoter or detractor probability and business metrics such as customer tenure, lifetime value, net operating revenues, etc. The next section illustrates some results from a case study based on this method.

Results: A Financial Service Provider Example

In this example, a financial service provider has a call center where service agents take calls from customers about their accounts, servicing issues, problems or changes they would like to make. The service provider has sent out a survey to a sample set of customers asking about their likelihood to recommend the service to others. The survey questions could be answered with “yes,” “no” or “neutral.” The provider combined these survey results alongside its structured customer data (such as account ID, customer tenure, revenues, etc.) as well as with related notes from its call center agents. This combined data set is 72,900 rows. Each row corresponds to a unique customer and has fields containing the call notes, survey responses and structured customer data.

Figure 6 depicts the text and data mining activities performed on the data set, as defined in Figure 5. This flow diagram indicates that the data was first randomly split into three groups – training, validation and test data sets, using the data partition node. The training and validation data was used to develop and fine-tune the model. And the test set is a hold-out sample that is not used to develop the model but is applied at the end of the process to validate the model results. It simulates how new data records will be scored with the resultant model, testing the robustness of the developed algorithm.

Figure 6: Data and text mining process flow using SAS® Enterprise Miner™ and SAS® Text Miner.
The third node in the diagram is the text parsing node. This node analyzes the call center notes text fields and parses the words, phrases and entities using NLP methods to identify nouns, noun groups, verbs, adjectives and the like. It also performs word stemming and entity extraction. The organization’s custom synonym lists provide explicit, predefined classification of terms, like product names, acronyms and slang words. Next, the text filter node checks spelling and determines which words have high frequency versus low information in relation to the target response variable (which, in this case, is the promoter score category). The text filter node filters low-frequency count terms; it is followed by the text cluster node, which creates numeric representations of the text data as SVDs.

Once structured, the text data is included in several different predictive models. In particular, the text data is included in two gradient boosting nodes, a logistic regression node, a neural network node, a text rule builder node and an ensemble modeling node (to the right of the neural network node). Next, results from each of these models are evaluated using a model comparison node. This creates diagnostic statistics that describe how accurately each model predicts the target (the promoter response).

Using the selected model, and based on the compared fit statistics from the model comparison node, a score node is applied to collect all the previous analytic routines (including both the unstructured and structured analysis methods used for developing the selected model). The score node is applied to new (not previously used) customer data records. For our financial services example, the text rule builder model outperforms the others. This is illustrated in Figure 7.

![Figure 7: Lift chart and fit statistics comparing alternate models that predict promoter scores.](image)
The receiver operator curve (ROC) index represents the area under the lift-chart curve – with a perfect model accounting for all variability and having a value of 1.0. In this example, the text rule builder achieved an ROC score of 0.872, (the highest ROC index), as shown in Figure 7. This means that the text-rule builder model is the best predictor of promoter score associated with this data. A comprehensive description of this model is beyond the scope of this paper, but we will note that this modeling method considers only unstructured text (not structured data) in the calculation.\(^3\)

Figure 8 depicts the text-ruler builder model actual versus predicted percentages for each level of the promoter score category. The main diagonal bars indicate correct classifications by the model; all other bars are considered misclassifications. The inset table shows the values of each bar in the chart.

![Figure 8: Actual versus predicted promoter score proportions.](image)

The following figures transform the predicted scores, describing them in relation to other key customer measures. Figure 9 shows the relationship with average customer value (log scaled), while Figure 10 shows the relationship with average customer tenure (i.e., the average length of time the customer has been with the company) from the aggregated results.

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\(^3\) A description of the Text Rule Builder modeling node can be found at: blogs.sas.com/content/text-mining/2012/10/08/active-learning-model-building-via-man-machine-cooperation. A more detailed description is available at: support.sas.com/documentation/cdl/en/tmgs/65668/HTML/default/viewer.htm#n0gozcx6nce3en157eybavu7eeu.htm.
Figure 9: Scaled customer value by promoter category.

Figure 10: Average customer tenure by promoter category.
From the previous figures, we see that the predicted promoter values are higher for those customers that have higher value and longer tenure than those predicted as passives. Similarly, we see that predicted passive customers have higher value and longer tenure than those predicted as detractors. While these may be expected results, in some industries (such as wireless telecommunications), these trends are reversed. This is due to the nature of that particular market’s competition and the relatively low margins in consumer-oriented businesses.

Figure 11 shows the general relationship of the model’s predicted promoter probabilities versus average customer tenure. A general trend upward is apparent, indicating (perhaps not surprisingly) that an increase of tenure also gives rise to an increase in promoter probability. But a much more revealing relationship emerges when the same chart is fitted with nonlinear econometric models and delineated by the active, guest and inactive customer groups – as shown in Figure 12.

![Graph showing the general relationship of promoter probability vs. customer tenure.](image)

*Figure 11: Mean probability of promoter versus average customer tenure. (Blue dots are aggregated data points; crosses are counts on the right vertical axis.)*
Figure 12: Fitted nonlinear econometric models showing average probability of promoter versus average customer tenure. (Red = Inactive; Green = Guest; Blue = Active.) Areas contained within the dashed lines represent 90 percent confidence interval bands.

Figure 12 shows a significant and distinct relationship between promoter probability and both customer tenure and degree of activity. It also reveals that you can use fitted econometric models to simulate what-if scenarios that help answer business questions such as: If X number of customers are moved up the promoter probability curve by Y percent, how much might customer tenure be affected?

We can derive additional intelligence from this analysis, too. Looking back at our text and data mining flow in Figure 6 (the process that turned the unstructured data into SVD values), we noted that we also created clusters of the call notes into similar themes, with “like” documents being grouped together. We achieved this using the text cluster node.
We can do simple hypothesis testing between promoters and detractors using the key word/phrase summaries of these clustered document profiles. In Figure 12, we see that each curve has a slightly different model and fitting parameters. For the red curve, representing inactive customers, the following is the model equation that fit this data (log is the natural logarithm):

\[ \log(P) = b_0 + b_1 \bar{c}t \]

where \( P \) is average probability of a promoter and \( \bar{c}t \) is the average customer tenure.

Figure 13 shows how all three of the customer groups illustrated in Figure 12 fit this log probability of being a promoter.

| Customer Group | Equation Number | Fitted Equation | Estimate \( b_0 \) | Estimate \( b_1 \) | Std. Error \( b_0 \) | Std. Error \( b_1 \) | t-Ratio \( b_0 \) | t-Ratio \( b_1 \) | Prob. > |t| \( b_0 \) & \( b_1 \) |
|----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Inactive       | 1               | \( \log(P) = b_0 + b_1 \bar{c}t \) | -4.41           | 5.55e-3         | 0.0553          | 8.12e-5         | -79.74          | 68.71           | .0001, .0001    |
| Guest          | 2               | \( \log(P) = b_0 + b_1 \bar{c}t \) | -12.63          | 8.54e-3         | 1.1788          | 8.37e-4         | -10.71          | 10.20           | .0001, .0001    |
| Active         | 3               | \( \log(P) = b_0 + b_1 \bar{c}t^2 \) | -4.433          | 2.37e-3         | 0.0397          | 2.42e-5         | -111.6          | 97.96           | .0001, .0001    |

Figure 13: Fitted equation statistics from the results of Figure 12. (Equation 1: Red = Inactive; Equation 2: Green = Guest; Equation 3: Blue = Active)

When we plot the average probability of a promoter versus the average customer value (which is scaled and transformed using a log function), we expect a model that shows how the probability of a promoter will increase (from say 0.6 to 0.75) related to corresponding changes in customer value. Since this curve is nonlinear, its slope changes as the customer values change (i.e., the slope is not constant).
Figure 14: Fitted nonlinear econometric models showing average probability of promoter versus scaled log customer value. (Blue = actual data aggregates. Red = fitted model.)

Figure 14 shows that the average probability of a promoter versus the scaled-log of customer value (in this case log is log-base 10) indicates that if the probability of a promoter changes from 0.5 to 0.7, the average value of a customer moves from 1.76 to 2.6. Moreover, this model has a different type of equation as its model fit, and is nonlinear – with the red line and red dots illustrating the model fit. The equation below indicates that $\theta_1$ equals 2 from the model fitting illustrated in Figure 14, and therefore the average probability $\bar{P}$ is actually a quadratic with respect to the average customer value $\bar{cv}$.

$$\bar{P} = \bar{\theta}_0 \times \bar{cv}$$

where $\bar{\theta}_0 = 0.125$ and $\bar{\theta}_1 = 2.0$
With the equations of the table in Figure 13, you can perform a simulation. The business question to ask is: How much change in the horizontal x-axis produces a change in the vertical y-axis? In econometric terminology, this change in x that produces a change in y is defined as elasticity. For linear models, this change can be just the slope of the line multiplied by x/y.

However, for nonlinear models, the elasticity is not constant and the slope changes as x changes – so the slope has to be determined at each point. Estimates of these slopes will help to answer the business question: If a change in average probability of a promoter is increased from 0.6 to 0.8, how much change in average customer tenure will result? For example, from Figure 12, if we look at the active customers with the blue curve, the change in average probability of promoter goes from 0.50 to 0.70 and produces a change in average customer tenure from 1,600 to 1,700 days. This is a 6.25 percent average net improvement. A similar change in average customer value (shown in Figure 14) produces an average customer value improvement of $505.00; an approximately 15 percent average improvement over the average lifetime tenure of the customer!

Conclusions

This paper proposes a strategic analytic road map for how SAS enables you to use promoter score survey results to identify customer migration value. After aggregating the scoring results of both the text mined model and the predictive data mining model, you can use econometric models to examine new visualizations of the relationship between promoter probability and metrics such as customer tenure and customer value. Then, you can combine simulation results with these aggregate econometric models to provide quantified financial and business impacts of migrating customers from one level of promoter probability to another.

The strategic value that your organization gains from such analyses enables you not only to understand why customers are or are not likely to promote your product or service – but also their likelihood to do so in the future. And you can do this with quantified confidence. As a result, your organization will be prepared to make trade-offs to address customer issues and their estimated influence on the business. You will be empowered to make fact-based decisions about the investment effort required to resolve your issues.

For More Information

For more information about analytical methods and products (including text mining, data mining and forecasting), visit: sas.com/technologies/analytics

For SAS solutions specialized in delivering customer insight, see: sas.com/ci

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