Tap into the true value of analytics
Organize, analyze, and apply data to compete decisively
Preface
From the Editors’ Desk

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Switching from bank to bank requires surprisingly little impetus for many consumers—a slightly higher savings rate, a free bonus offer, or a non-satisfactory customer service call. Years of investments on customer acquisition have left many banks wide open to attrition—existing customers feel unwanted and competing banks appear attractive. To combat this “grass is greener” syndrome, it is critical that banks shift their focus to customer retention. This article attempts to provide a solution to customer attrition through the application of analytical techniques.

**Introduction**

The issue of attrition is an area of serious concern for the financial services industry. Though some banks measure customer defections, relatively little effort is invested in retaining customers. This is unfortunate, because customer defection has become one of the most illuminating measures in business. It is the clearest possible sign that customers see a deteriorating stream of value from a company. Attrition is more than a number—it can hit a bank severely in terms of revenue and income growth.
Attrition can be controlled using various methods. The most effective technique is also probably the most straightforward: understand the customer, and leverage this understanding to provide exceptional service and maintain a good relationship. This is possible only when a customer’s behavior is known or examined.

Analytics provides this window into customer behavior by leveraging the analysis of historical data. In the absence of analytics, banks are often reactive rather than proactive—defining strategies only when customers are most likely to attrite, so as to win back their confidence. Unfortunately, these situation-dependent approaches can only help resolve problems temporarily. In attrition scenarios, analytical techniques play a crucial role in assisting banks to manage attrition better. Analytics transform the business objective into a data-driven problem, which can be solved to arrive at the final solution/recommendation.

Defining an Analytics Approach

Analytical techniques—such as customer profiling and predictive modeling—hold great promise as powerful tools to enhance customer retention and to manage the problem of attrition. In general, the crux of determining a possible solution to a problem is to take a structural approach towards attaining the solution. The concept of attrition should be viewed in multiple business perspectives to decide on the optimal approach. The objective is not only to retain customers, but also to improve profitability and increase their lifetime value. To achieve better customer retention a sequential approach is required:

- Determine the root causes of customer churn
- Define strategies that induce churn reduction
- Successful implementation of said strategies

The above-mentioned approach will help drive customer retention to a large extent. The prime challenge is to transform this approach into a practically applicable analytical solution.

Predictive Analytics

Predictive analytics utilize statistical models that predict the attritional behavior of a customer by generating risk scores. This is followed by profiling customers based on reasons for attrition through cluster analysis.

The above-mentioned approach can be explained by hypothetically applying the technique on a representative bank’s portfolio (XYZ):

- The transactional behavior and other attributes associated with the customer are examined, and used for predicting the possibility of attrition.
- A statistical model is built on the data collated (the transactional behavior and the demographic attributes of the customer) to predict the probability of attrition of a customer.
- Deploying this technique not only provides an alert to Bank XYZ stating that there are customers who are likely to end their relationship, but also helps in identifying such customers.

Logistic regression is used for building the predictive model through which predictive scores are generated for the customers. These predictive scores quantify the risk
The intention of performing this analysis is to identify the group of customers who have a higher probability to attrite, so that the bank can take corrective measures to retain them. This decisive and significant information is inferred from the predicted attrition scores for all the customers. In our hypothetical case, a higher score implies higher possibility of customer attrition.

The model performance is also validated using robust validation techniques and diagnostics. Figure 1 (on the next page) illustrates the model's predictive power.

In Figure 1, the Kolmogorov-Smirnov (K-S) statistic measures the difference between the percentages of attritors and non-attritors of the sample distribution. Lift is a measure of the effectiveness of a predictive model, calculated as the ratio between the results (probabilities) obtained with and without using the predictive model. A Lift Curve is also used to track a model's performance over time, and to compare a model's performance across different samples. The stability aspect of the model is measured through the Population Stability Index (PSI) that portrays the stability of the model over time.

The predicted attrition scores from the above model provide comprehensive information on the customers' behavior towards the bank. If the scores are way too

<table>
<thead>
<tr>
<th>Critical customer variables</th>
<th>Table 1</th>
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<tbody>
<tr>
<td><strong>Variable</strong></td>
<td><strong>Description</strong></td>
</tr>
<tr>
<td>Income</td>
<td>Annual Income of the Customer</td>
</tr>
<tr>
<td>No. of Accounts</td>
<td>Total No. of Accounts Held by the Customer</td>
</tr>
<tr>
<td>Customer Age on Book</td>
<td>No. of Months Customer has Relationship with the Bank</td>
</tr>
</tbody>
</table>
high for a highly valued customer, they indicate a trigger to the bank that if the scenario is left unnoticed, the chances are quite high that it might lead to attrition. This in turn will drive revenue loss. These predicted scores, along with other available customer information, are used for performing a cluster analysis to segment customers and apply strategies.

**Step 2: Cluster Analysis**

The clustering procedure is based on the K Means Method of Clustering. In the K Means method, the algorithm runs on an iterative mode. The premise for the iteration is the assignment of a data point to each cluster, based on the minimum Euclidean distance from the K-cluster centroids to the data points. The cluster centroids become more refined as the data points in each cluster change based on minimum distance calculation. For a good clustering solution, the within cluster homogeneity and between cluster heterogeneity should be high.

In this hypothetical example, Proc Standard along with Proc FastClus were used in SAS to generate clusters, after which profiles were created based on the resultant clusters. Five clusters were generated based on the reason for attrition, and their profiles are described in Figure 3. The reasons for

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**Customer Profiling using Cluster Analysis**

Cluster analysis is used to segment the entire customer population based on demographic and transactional behavior. Figure 2 depicts the steps involved in performing the analysis.

**Step 1: Data Compilation**

Step 1 involves the collation of behavioral, demographic and transactional information as mentioned above. The data describing the reason for attrition of a customer in the past is also collated for cluster formulation.

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<table>
<thead>
<tr>
<th>Attrition model performance measures</th>
<th>Figure 1</th>
</tr>
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<tbody>
<tr>
<td><strong>Attrition Model KS and Gains Curve</strong></td>
<td></td>
</tr>
</tbody>
</table>

![Attrition Model KS and Gains Curve](image)
### Cluster profiles

| Cluster - 1 | Demographics: 40+ years Aged Customers, Age on Books is More Than 10 Months, Unmarried, Average Income is US $150K.  
**Products with Highest Transaction Frequency and Amount:** Cash credit, Current Account, Loan and Savings.  
**Risk Profile:** Low Risk (Based on Risk Score Generated). High Avg Loan Balance, High Overdraft and Loan Relationship Size. |
| Cluster - 2 | Demographics: Customer's Average Age is 30 years, Average Age on Books is 5 Months, Unmarried, Average Income is US $40K.  
**Products with Highest Transaction Frequency and Amount:** Over Draft.  
**Risk Profile:** High Risk (Based on Risk Score Generated). High on Over Draft, Highest on Current Account Balance, Most Fees Generated out of Current Accounts, More Risky (Worst Bureau Score). |
| Cluster - 3 | Demographics: Customer's Average Age is 30 Years, Average Age on Books is 5 Months, Unmarried, Average Income is US $35K.  
**Products with Highest Transaction Frequency and Amount:** Cash Credit, Credit Cards and Savings.  
**Risk Profile:** Low Risk (Based on Risk Score Generated). High on Cash Credit, Credit Card Balance, High on savings, Highest Fee Generation from Cash Credit. Good Bureau Score. |
| Cluster - 4 | Demographics: 45+ years Aged Customers, Age on Books is More Than 20 Months, Mostly Married, Average Income is US $140K.  
**Products with Highest Transaction Frequency and Amount:** Credit Card, Current Account.  
**Risk Profile:** Low Risk (Based on Risk Score Generated). High Avg Credit Card Balance, High Over Draft balance, High Current Balance and High Relationship Size Across Credit Cards, Over Draft and Current Account. |
| Cluster - 5 | Demographics: 40+ years Aged Customers, Age on Books is More Than 12 Months, Married, Average Income is US $160K.  
**Products with Highest Transaction Frequency and Amount:** Loan, Savings and TD.  
**Risk Profile:** Low Risk (Based on Risk Score Generated). High Loan, Term Deposit and Savings (Highest). |
attrition were examined from the collated data, and the prime reasons were identified by analyzing the attrited customers. The three key reasons which were specified by the hypothetical customers were:

- Not being recognized as a valuable customer
- Unhelpful staff
- Ineffective customer care service

**Step 3: Validation of Clusters**

The generated clusters are validated in terms of accuracy and practical application. The clusters' accuracy over time is validated by calculation of the PSI, which tells the stability of the generated clusters over time. Figure 4 depicts the PSI for the hypothetical clusters generated.

**Step 4: Suggestions/Strategies**

The results of the cluster analysis yielded cluster profiles portraying customer behavioral and demographic characteristics. These characteristics are predominantly used for strategic decision-making for customer retention. On examining the clusters, it was found that customers aged 40 and above are less risky compared to customers of the average age of 30 years. The low risk customers can be offered a loyalty program—in the form of special discount offers or reward points that can be redeemed.

The customers who are more risky can be handled in a different way based on their product usage and transactional behavior. For example, they could be offered a different product which serves to improve their creditworthiness. On examining the clusters, it can be inferred that the risky customers transact more on overdraft and hence, to avoid any potential risk of attrition, those customers could be offered a savings product so as to build a long-term relationship. The above proposed strategies would definitely help the hypothetical bank maintain a better customer relationship.

**Conclusion**

Low switching costs, a lack of trust, and deteriorating customer service have pushed many customers away from their banks.

<table>
<thead>
<tr>
<th>Cluster</th>
<th>Development</th>
<th>Validation</th>
<th>PSI</th>
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<td>%Obs</td>
<td>#Obs</td>
</tr>
<tr>
<td>1</td>
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<tr>
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<td>17.6%</td>
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<td>3</td>
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<td>63</td>
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<td>16</td>
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<tr>
<td>5</td>
<td>88</td>
<td>23.5%</td>
<td>32</td>
</tr>
<tr>
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<td>125</td>
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</table>

PSI for the Clustering Model = 0.0142 < 0.1, hence, Model Stable Over Time
In the financial services industry, attrition is a major problem with very real impacts on the bottom line. To combat attrition, proactive banks are turning to analytics to study the attrition behavior of customers and to deploy various attrition-battling strategies. These range from providing free checking accounts, to promoting online banking and improving customer service. Each has one goal in mind: improve customer retention—a key component for driving future revenue growth and profitability.
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