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Customer Experience Modeling

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ABSTRACT

Companies with large customer bases and high volumes of service interactions often have a number of customers who experience a service failure. The impact on these customers involved can be significant, and has the potential to be disproportional to the root cause of the incident. For complex and dynamic businesses, the continuous introduction of new products and services can create conditions where there are increased opportunities for suboptimal customer service outcomes. The authors have employed predictive analytics to provide the business with an opportunity to remediate these issues before the customer feels compelled to take action.

Building robust sources of customer interaction data and an automated scoring environment has made it possible to deliver highly effective 'customer dissatisfaction' scores to front of house. This provides a valuable 'last chance' opportunity to solve serious customer service issues.

INTRODUCTION

Retailers often employ predictive modeling to improve the effectiveness of direct marketing campaigns. By using customer data from a range of sources, various modeling techniques can be used to identify the association between patterns of customer behavior and a specified outcome (e.g. product sale, service abandonment, defection to a competitor). Marketers use these models to direct specific communications to customers with the aim of influencing the likely outcome (e.g. close the sale, prevent the defection, encourage the take up of value added services). Many companies also aim to provide uniformly high levels of customer service to what are often very large customer bases sometimes in excess of 10 million customers. While aiming for excellence in customer service, many organizations must deal with a high volume of customer interactions across multiple channels and products.

LOOKING FOR ROOT CAUSES OF POOR CUSTOMER EXPERIENCE

Businesses with a large customer base and high volumes of service interactions are likely to have a number of customers who 'fall through the cracks' and are impacted by service incidents regardless of a company's focus on customer service. The resulting poor service experiences often result in increased customer defection rates, complaint volumes, inbound call volumes (repeat calls), and reduced profitability, Life Time Value and customer advocacy. There are also implications for brand image. Even relatively small occurrences of incidents can cause severe impacts on the customers and the business.

To protect customers against these incidents and to minimize the associated impact on the brand, businesses tend to focus on tracking customer interactions leading up to the incident in order to identify root causes. Monitoring correlations between the volume of complaints and a variety of other business metrics (sales volumes, product type, sales channel, interaction type etc.) is a technique frequently employed to alert the business to new problems and to track the success of activities employed to rectify problems.

Market Research also plays an important role in helping company's understand the cause of poor customer experiences. The results of customer interviews and surveys can uncover more complex root causes to issues which may be difficult to identify from internal data alone.

THE CHALLENGE TO ELIMINATE ROOT CAUSES

In business sectors where customer interactions, services and products remain relatively stable over time, organizations have an opportunity to build and maintain robust processes which guarantee consistently high levels of customer service. In other words, the root causes of customer dissatisfaction can gradually be reduced or eliminated over time. However, most businesses exist in competitive environments which rely on the introduction of new products and services for continued growth. Organisations need to focus on both increasing operational efficiency and improving customer service to be competitive.

Although different companies deal with these issues with varying degrees of success, the fast rate of change is generally associated with higher levels of risk: the introduction of new root causes leading ultimately to customer dissatisfaction reflected in increased rates of inbound calls, more incidents of case management, higher rates of churn and a plethora of other negative business impacts. In rapidly moving industries like telecommunications the constant introduction of new technologies, products, pricing and service offerings tend to deliver a small but continuous stream of new 'root causes' which lead to bad customer experiences.

Programs that continuously monitor, identify and remediate root causes are essential if high levels of customer satisfaction, loyalty and advocacy are to be maintained.

While these programs help to remove the root causes of poor customer experiences, they may not be able to identify or help customers already impacted. These customers are already on a path which, unless corrected generally leads to the aforementioned customer and business impacts. At Telstra we have employed predictive modeling as a way of providing the business with an opportunity to identify customers who have had a suboptimal experience before they react by either terminating the relationship or lodging a complaint. The challenge for the modeler has been to identify what, from a statistical point of view, is usually a rare event and one which can occur over a relatively short period of time. The challenge for the business has been to ensure that this information is delivered in a timely manner and that the processes necessary to take appropriate action are in place.

BUILDING AND DELIVERING THE MODEL

Choosing an appropriate target group for modeling is usually based on the specific business requirement. In this case the imperative was to reduce the number of complaints being lodged by customers. As a result a modeling data set containing a representative number of customers who had lodged a complaint was constructed. Any other negative customer impact (e.g. repeat inbound calls, churn) could have been used as the target variable, however the stated business aim at the time was to reduced the number of customers who felt they had no option other than to lodge a complaint.

A range of variables was considered for inclusion and consideration as part of the modeling process, these included:

- Customer demographics (e.g. customer age, tenure, household income etc)
- Products and billing data (e.g. product holdings, mobile plan types, spend levels etc)
- Customer interaction data (e.g. inbound calls, outbound calls, emails, volume of interaction, previous complaints etc)
- Service orders, requests and faults
- Payment history

The model was built and scored using SAS ® Enterprise Miner, SAS ® Model Manager and SAS ® Scoring Accelerator for Teradata ®.

One of the technical challenges of delivering a model which relies on a broad range of data sources and accurate timing is its integration with existing business processes and systems. Without adequate integration, the predictive power of the model can be wasted if action cannot be taken within the necessary timeframe (i.e. before the customer lodges a complaint, abandons their service etc.) These challenges are magnified in environments consisting of a mix of legacy systems and new customer oriented architectures. It was necessary to understand the data latency and work with the call centers to ensure customer lists were delivered to 'Front of House' with sufficient time for intervention.

UNDERSTANDING TIMING - THE PREDICTION WINDOW AND INTERVENTION

One of the most important factors to be considered during the design of the model was the timeline consisting of receiving customer data, scoring and prediction, delivery to operational systems and intervention. The model needed to be built with some “delay” to allow for the gap between customer data becoming available and the earliest possible intervention at ‘front of house’. In this case, the development of the model focused on being able to predict the lodgment of complaints two weeks in the future. This allows time for relevant data to become available in operational systems, and provides time to run the model and produce the list, in addition to providing an extra week for intervention. Table 1 shows an example:

Data currency	Customer scored	List produced & sent	Opportunity to intervene	Predicted target complaints
Friday	Wednesday	Thursday	Friday to Thursday	Friday to Thursday
27-Jan	1-Feb	2-Feb	3-Feb to 9-Feb	10-Feb to 16-Feb

Table 1. Timing of key events in the delivery of the model.

Another factor which was taken into consideration during the design of the data structure is how previous incidents can influence the likelihood of customers lodging a complaint at a future time. The modeling dataset was constructed from customer behavioral information (eg. Inbound calls, previous complaints made) over a range of time periods.

RESULTS

Results generated from back testing, (scoring historical data and the examining the outcomes i.e. did the customers predicted actually lodge complaints) showed that the model was delivering strong results for high risk customer groups identified as being most at risk of lodging complaints. Table 2 shows that the 5% of customers with the highest scores actually accounted for 34% of the complaints lodged. (In a random sample of customers the expectation would be that 5% of complaints originate from a customer group of this size). This result is expressed as a ‘lift’ or improvement over the expected outcome from a random sample of customers. In this case, the results were seven times better (or more predictive) than a random sample. Similarly the results from the highest scoring 10 per cent and 30 per cent of customers are also shown. As expected, with greater volumes of customers scoring lower in the model the benefit (lift) delivered reduces.

	Cumulative % captured response	Cumulative lift
Top 5%	34%	7 times
Top 10%	49%	5 times
Top 30%	77%	2.6 times

Table 2. Initial test results for the model.

In this model the top 5 per cent of customers actually represents approximately 300,000 customers. While only a very small proportion of these will actually go on to lodge a complaint during the outcome window (< 0.03%) the model gives the business an opportunity to provide a enhanced service experience to these customers in order to uncover and address any service difficulties they may be experiencing.

STABILITY OF MODEL COMPARED TO ROOT CAUSES

The advantage of a model able to identify 'at risk' customers is that it has the potential to be relatively stable over time. Conversely the root causes of poor customer experience tend to change. Once identified, they are solved but over time new ones tend to be inadvertently introduced.

This means that even though the root causes of dissatisfaction change over time, the patterns of behavior exhibited by affected customers tend to remained relatively stable.

Customers impacted by poor service experience have their own unique set of circumstances, however these tend to result in a predictable set of behaviors and interactions with the business. This is why the model works.

While every customer is assigned a new model score each week, the actual predictive power of the model is also monitored on a monthly basis through back testing (i.e. the process of assessing what proportion of predicted outcomes actually eventuate). The model has been in operation for almost a year and ongoing performance monitoring has demonstrated its stability over time. Table 3 shows one of the more recent performance results and when compared to the previous results in Table 2 generated just after the model was initially implemented it shows long term consistency in performance.

	Cumulative % captured response	Cumulative lift
Top 5%	36%	7.2 times
Top 10%	56%	5.6 times
Top 30%	70%	2.1 times

Table 2. Recent test results for the model.

Over the same period of time 'root cause' analysis shows that the mix of root causes driving complaints has varied markedly. In fact material changes in the mix of root causes is evident even over the period of a few months.

COMBINING THE MODEL WITH A TRIGGER – MOVING TOWARDS 'REAL TIME' EXECUTION

Although the model provides a practical method of identifying and assisting customers, more recent work has shown that the predictive power of the model can be improved further by combining this approach with more timely customer interaction data.

Real time scoring of the customer at the point of interaction (inbound call in this case) for their likelihood to lodge a complaint should provide a more accurate result. This would in effect remove the data latency delay built in to the current model and allow us to consider all available customer data up to the point of interaction.

An analysis of customer initiated inbound calls (Recent Interaction) in the week immediately preceding the 'Opportunity to Intervene' week shown in Figure 1 demonstrated that reducing data latency resulted in more accurate identification of customers at risk of lodging a complaint .

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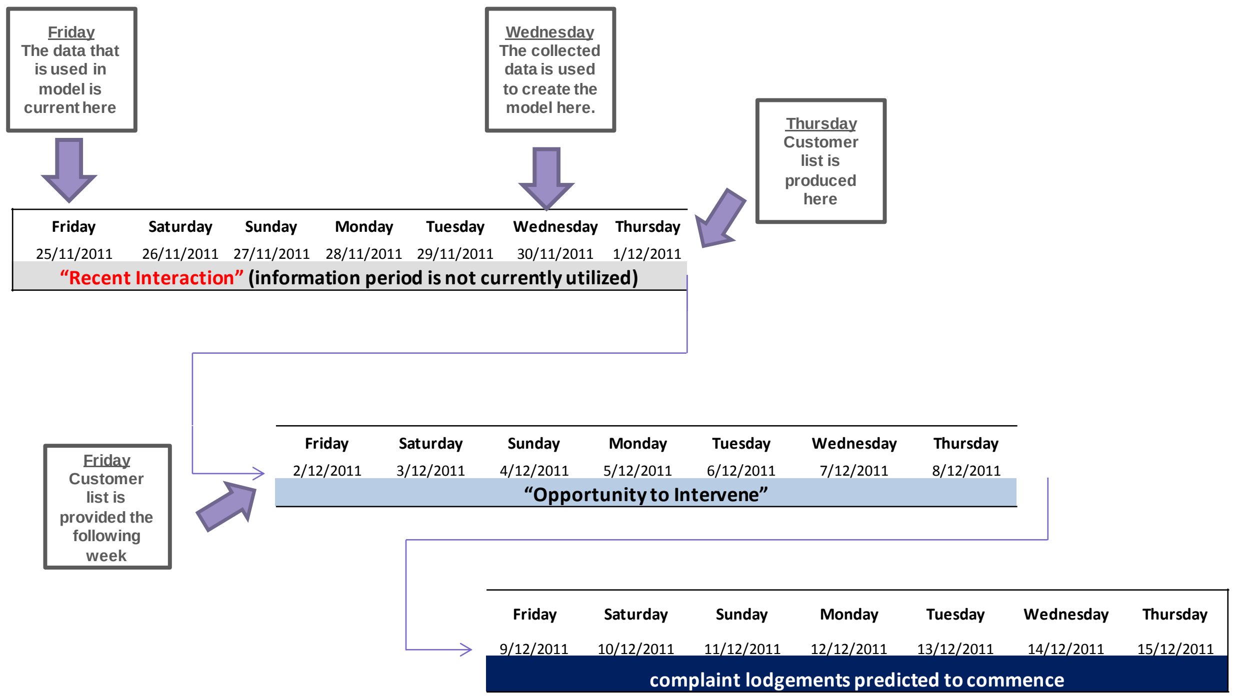

Figure 1. Model Timing

This work identified a much smaller group of customers representing less than 1 per cent of the population with a likelihood of lodging a complaint approximately 17 times that of the average customer (around 2.5 times more likely than the top 5% of customers identified using the model alone).

Importantly the 'trigger' criteria which was defined in this analysis (customers with more than 2 inbound calls occurring in the "Recent Interaction" week) can be applied to the final model scores and used to further refine the list delivered to 'Front of House' to use in the "Opportunity to Intervene" week identified in Figure 1.

The analysis supported the proposition that when combined with the model, interaction data closer to the event as a trigger can boost the prediction and result in more accurate targeting of a very high risk group of customers where intervention and resolution is imperative.

It is expected that customers in this group who do not lodge complaints are still very likely to be suffering from serious customer service issues which warrant proactive resolution. Even when complaint lodgment does not occur the associated impacts of poor customer experience are still likely to occur, for example increased customer defection rates, complaint volumes, inbound call volumes repeat calls, decreased profitability, Life Time Value and customer advocacy

EXECUTION CHANNELS

It has been essential to work with the call centre teams to validate the predictions and ensure the accurate identification and treatment of the 'at complaint risk' customers. The top 300k customers are routed to specialist agents and a "Customer Care Alert" note is triggered when the agent answers a call from one of these customers.

Results have been very positive and have shown lower transfers, lower pre-complaint interactions (interactions with customers that go on to lodge complaints) and a reduction in complaints.

The implementation of the model to date has focused on intervening when a 'high risk' customer is identified on an inbound call. This passive approach has largely been due to the relatively high volumes of customers identified in this group. The work to include the 'Recent Interactions' trigger in the model has resulted in the identification a smaller group of high risk customers (~25,000). These smaller customer numbers mean that proactive (outbound) communications becomes a practical option, rather than simply waiting for them to contact the business again.

CONCLUSIONS

The business is committed to removing sources of customer dissatisfaction from internal processes and customer touch points. There are several major initiatives directed to this end as well as the drive to continuously improve customer experience. Nevertheless, it would be unreasonable to assume that it will be possible to remove every potential source of complaint. There will always be customers who, for a variety of reasons, (some of them extremely rare events) are inadvertently exposed to a suboptimal interaction with the business. It is therefore prudent to put in place processes designed to redress these issues at the earliest possible opportunity. This model and the associated people, processes and systems that support its operation are an important and effective part of this program.

The model's demonstrated ability to identify customers with high levels of dissatisfaction stemming from a variety of changing root causes as well as its stability over time makes it a valuable and practical commercial tool helping to protect the relationship between customer and business.

The later work combining the model with inbound call triggers further reinforces the commercial value of this work. The authors believe that further opportunities exist in the analysis of other short time frame customer events (triggers) and their interaction with this model as well as other predictive models (eg. Defection, Abandonment, Cross Sell, Recontracting).

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