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Operational Business Intelligence: Applying Decision Trees to Call Centers

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ABSTRACT

In this paper we propose a decision tree based approach to modeling service levels in insurance call center operations. Our approach allows call center managers to determine which factors they control have the greatest impact on service levels (ex. handle time, average hold time, etc.). We also propose a sliding window to allow managers to interpret the effects changes in resource allocations have on service levels. To test our solution we analyze data collected from a large U.S. insurance company. The initial results provide good insight into factors affecting service levels.

Keywords

Business intelligence, service levels, call center, decision trees.

INTRODUCTION

Calls centers are key organizational structures in a wide variety of industries, including the insurance industry (Callaghan and Thompson 2001). Call centers were developed based on the queuing principles developed by Agner Krarup Erlang (Angus 2001) and others, principally the pooling of capacity (servers) and methods by which the incoming call distribution is used to determine the appropriate number of phone lines and staff based on the tradeoffs between costs and service quality (Townsend 2007).

There is disagreement on the purpose of call centers; two views are common. One view is call centers are used by organizations as a way to reduce operating costs with customer service delivery being a secondary consideration. On the one hand call center mangers believe their job is to manage call centers in order to maximize customer service (Robinson and Morley 2006) (Li et al. 2003). Despite how one views the purpose of a call center, the efficiency of a call centers is vital to the competitiveness of an organization (Lam and Lau 2004).

The efficiency and effectiveness of call centers can be improved by using and implementing innovative technologies and customer focused measures. Service levels measure the performance of a system. Service levels can measure items such as percentage of calls answered by a call center or percentage of customers waiting less than a fixed amount of time. Service levels are a common customer focused metric used frequently in insurance company call centers. A number of studies in the past have shown service levels to be a good indicator of customer satisfaction with call center experiences (Cronin et al. 2000).

Insurance companies have a unique property defined as “stickiness” or lock-in. Customers are less likely to leave or switch to another insurance company if they have a bad experience or are given low service quality versus many other business interactions (Keiningham et al. 2006). Switching cost is commonly the reason for “stickiness” since barriers to entry exist. Insurance companies cannot just use as their main metric the number of customers or number of calls answered a primary measure of call center quality. Doing so will measure something entirely different than call center service quality.

Companies collect large amounts of data to help manage call center operations. But, "unstructured data is growing at a rate of 15-35%" (The Taylor Research Group 2007) resulting in a classic situation where the ability to collect data has outpaced the ability to analyze data. Computer-based decision support models have the advantage of sharpening information-processing skills in general (Curry and Moutinho 1994). The importance of implementing business intelligence tools to analyze and use the data has not been realized in many organizations.

This paper demonstrates an operational implementation of a business intelligence tool as it relates to call center service levels in the insurance industry. We propose a decision tree based solution to provide timely knowledge regarding the most important (and often changing) factors that influence service levels. This allows managers to have real-time visibility in the operational effectiveness of managing the call center. Many Business Intelligence applications provide real-time visibility (Callaghan 2003), and this paper shows how an insurance company can have operational business intelligence.

Traditionally call center service levels focus on capacity optimization for a given input rate. The company data for this study shows that call volume is not significantly correlated with service levels, implying that capacity planning is adequate. However, capacity and call volume do not explain all variation in service levels leaving managers wondering what else affects service levels.

The goal is this paper is to show that using decision trees, a more effective model for improving service levels in call centers can be created. The results of this research provides a method for both researchers and practitioners who are interested in improving service levels for call centers.

CALL CENTER MANAGEMENT BACKGROUND

Call centers can be classified into three different levels, high value-added services, medium value-added services, and low value-added service levels; examples of each are shown below (Jobs et al. 2007).

Service type	Examples
High value-added services	Financial services/banking/insurance; Government. IT services/data bank;
Medium value-added services	Telecommunications Customer service Directory services/job placement
Low value-added services	Fulfillment/distribution/reservations; Telemarketing/collections.

Table 1: Example of Different Types of Value-added Services

A tremendous amount of work has been completed in the areas of simulation and modeling of call centers. Our paper is modeling call center performance, but we are focused on a managerial metric called service level. This is a marked difference between our research and previous studies. In the past efforts concentrated on answering operational questions such as (Mehrotra and Fama 2003):

- How many agents should we have on staff with which particular skills?
- How should we schedule these agents' shifts, breaks, lunches, training, meetings and other activities?
- How many calls of which type do we expect at which times?
- How quickly do we want to respond to each type of inbound call?
- How should we cross-train our agents?
- How should we route our calls to make the best use of these resources?
- Given a forecast, a routing design, and an agent schedule, how well will our system perform?
- What is our overall capacity?

Our study focuses on macro level performance issues in call centers, specifically service level. Some previous studies have looked at performance issues but their viewpoint is strictly from the manufacturing quality and efficiency point of view. For example, Omari and Al-Zubaidy (2005) discussed the performance metrics quality of service, and efficiency of call centers. They defined quality of service as the probability of blocking a customer call due to the unavailability of a trunk. Efficiency is based on agents' utilization and salary costs. This viewpoint of performance is markedly different from the one presented in this paper.

Historically operations researchers have used tools such as queuing theory (see Hampshire and Massey 2005), stochastic processes (see Garnett et al. 2002), and simulations (see Avramidis et al. 2004) to model call centers. In addition, some studies such as (Atlason et al. 2004) include an identical definition of service level as we use. However, they are not attempting to model service levels, but are trying to maintain a specific service level while modeling staffing costs. We are modeling a call-center process with service level as the criterion (many previous studies use criterion such as capacity or response time). This paper also differs because we are not using a traditional statistical technique, but are using binary decision trees. Our decision trees allow us to easily see the impact on service levels of independent factors such as call volume.

OPTIMIZATION OF CALL CENTER PERFORMANCE

The most common method organizations use to optimize call center performance is capacity planning. By making sure that the number of agents answering the phone meets the number of call coming in, a high service level can be achieved. But what is the next step? What do companies do after they have demand properly managed? The insurance company in this paper had its basic capacity management problems controlled. They have figured out optimal staffing levels, hours of operations, agents break schedules and lunches, and shift timing. In addition, agents' vacation requests and required training were considered to maximize service levels. Most call centers are high-pressure work environments (Houlihan 2000) where turnover is a major management problem. The insurance company has the staffing problems created by the job itself controlled.

DATA OVERVIEW

We analyzed hourly data collected from a call center provided by a national insurance company. As part of the agreement to gather the data, the identity of the firm is withheld. Managers for the call center concern themselves with factors affecting service levels. Our dependent variable, service level, is a proxy for the overall hourly performance of the call center.

The call centers also collect the following independent variables:
DATE: date of service

TIME: hour of day ranging from 9:00 AM to 7:00 PM (one hour increments)

ACD CALLS: The Automatic Call Distribution system (ACD) is a specialized telephone answering method that handles large volumes of incoming calls by distributing them equally among a group of agents on standard telephone lines (Lam and Lau 2004). The ACD call is a metric that counts the number of calls that are routed through this system. All calls are routed through the ACD system unless a caller hangs up almost immediately.

ABANDONED: Abandons are calls that enter the ACD system but the caller hangs up before being answered.

AHT: Average handle time is measured in seconds including the call time and wrap up time after the call concludes.

ASA: Average speed of answer is how many seconds a call center representative took to answer a routed phone call.

MAX DELAY: Maximum delay is the time in seconds the longest call waited until either answered or hung up.

The first step in setting up our decision tree is to calculate descriptive statistics and correlations for our variables.

	Mean	Median	Std.Dev.
SERVICELV	0.922	0.933	0.079
ACD CALLS	2008.485	1995.000	1269.089
ABANDONS	9.092	6.000	14.567
AHT	298.447	301.000	25.229
ASA	7.488	6.000	11.471
MAXDELAY	178.977	133.000	168.777

Table 2: Descriptive Statistics for Selected Variables

Variables date and time are not included in Table 2 because descriptive statistics do not apply, but they are transformed for use (see below). As can be seen the call center has an average service level of 92%, with a standard deviation of 8%.

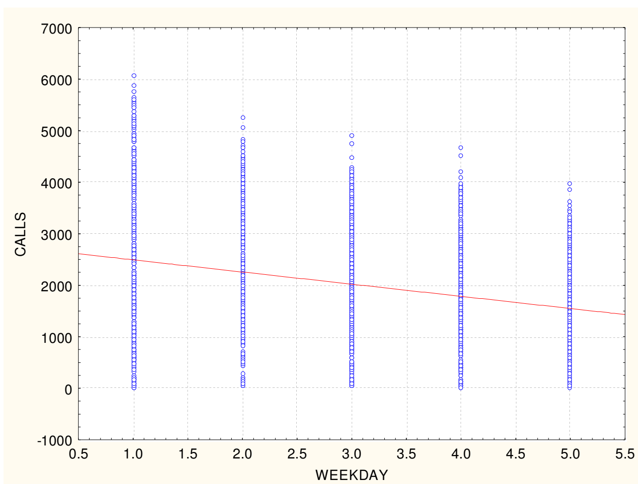

Figure 1: Call Volume vs. Weekday

Figure 1 above shows the distribution of calls by weekday. Volume steadily decreases from Monday to Friday (1-5).

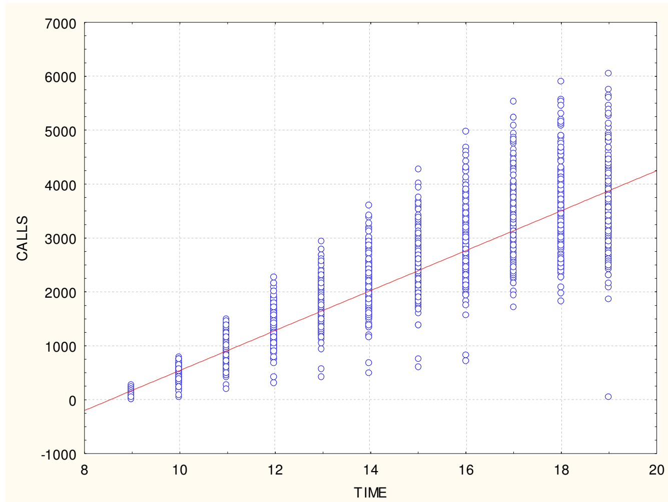

Figure 2: Call Volume vs. Time of Day

Figure 2 displays the distribution of calls by time of day and shows that call volume steadily increases during the day. Time of day is presented hourly using a 24 hour clock.

	DATE	WEEKDAY	TIME	SERVICELV	ABANDONS	AHT	ASA	MXDELAY
DATE	1.00	-0.02	-0.01	0.01	-0.04	-0.15	-0.05	0.11
WEEKDAY	-0.02	1.00	-0.01	0.16	-0.17	0.08	-0.13	-0.02
TIME	-0.01	-0.01	1.00	0.00	0.35	0.31	0.02	0.39
SERVICELV	0.01	0.16	0.00	1.00	-0.67	-0.07	-0.87	-0.42
ABANDONS	-0.04	-0.17	0.35	-0.67	1.00	0.14	0.76	0.51
AHT	-0.15	0.08	0.31	-0.07	0.14	1.00	0.06	0.14
ASA	-0.05	-0.13	0.02	-0.87	0.76	0.06	1.00	0.43
MAXDELAY	0.11	-0.02	0.39	-0.42	0.51	0.14	0.43	1.00

Table 3: Matrix of Correlations

A correlation analysis on all variables yields the results in Table 4. The results shows date and time do not correlate with service level although call volume correlates with both variables (at significance levels of .05 or less). Intuitively it makes sense that service level quality would suffer during high call volume times and excel during low call volume times. However, a quick analysis shows that is not the case. Although we have no data, we may speculate that good staffing practices may have caused this result. This is an important result to note because it tells us that we need to recognize other factors that explain variance in service levels.

To simplify the analysis, we remove predictor variables time and date, which analysis shows do not correlate with service levels. The revised data set includes: service level (SERVICELV), weekday, calls, abandons, average handle time (AHT), average speed of answer (ASA), and maximum delay (MAXDELAY).

ANALYSIS/ RESULTS

The first step in developing our proposed business intelligence system is to create a decision tree predicting service levels based on our independent variables. For our analysis, SERVICE LEVEL is the response variable, WEEKDAY is a categorical variable, and the continuous predictor variables are CALLS, ABANDONS, AHT, ASA, and MAXDELAY; 2738 valid observations spanning approximately 18 months exist for this data set.

Statistica's implementation of CART (classification and regression trees) was used to create our decision tree. CART is preferable to earlier decision tree algorithms because it provides greater explanatory power and the ability to associate levels of variable measures with a tree split (see Breiman et al. 1983).The resulting decision tree (**Figure 3**) provides key insights into which variables have the greatest impact on service levels. This is of key importance to managers so they can efficiently allocate scarce resources.

Constructing a decision tree and determining key factors is an important first step, but alone is not sufficient to provide continuing operational support to managers. What we propose is a system that uses a sliding window that continually reconstructs decision trees and highlights key factors impacting service levels. This is critical because as mangers reallocate resources the impacts individual variables have on service levels change. For example, we can envision a system that shows in near real-time how increased efforts to reduce average speed of answer impact service levels. The company data we have is summarized at the hourly level. Reports could be generated hourly, but once or twice a day is likely more appropriate so that changes in resource allocations have time to appear in the data.

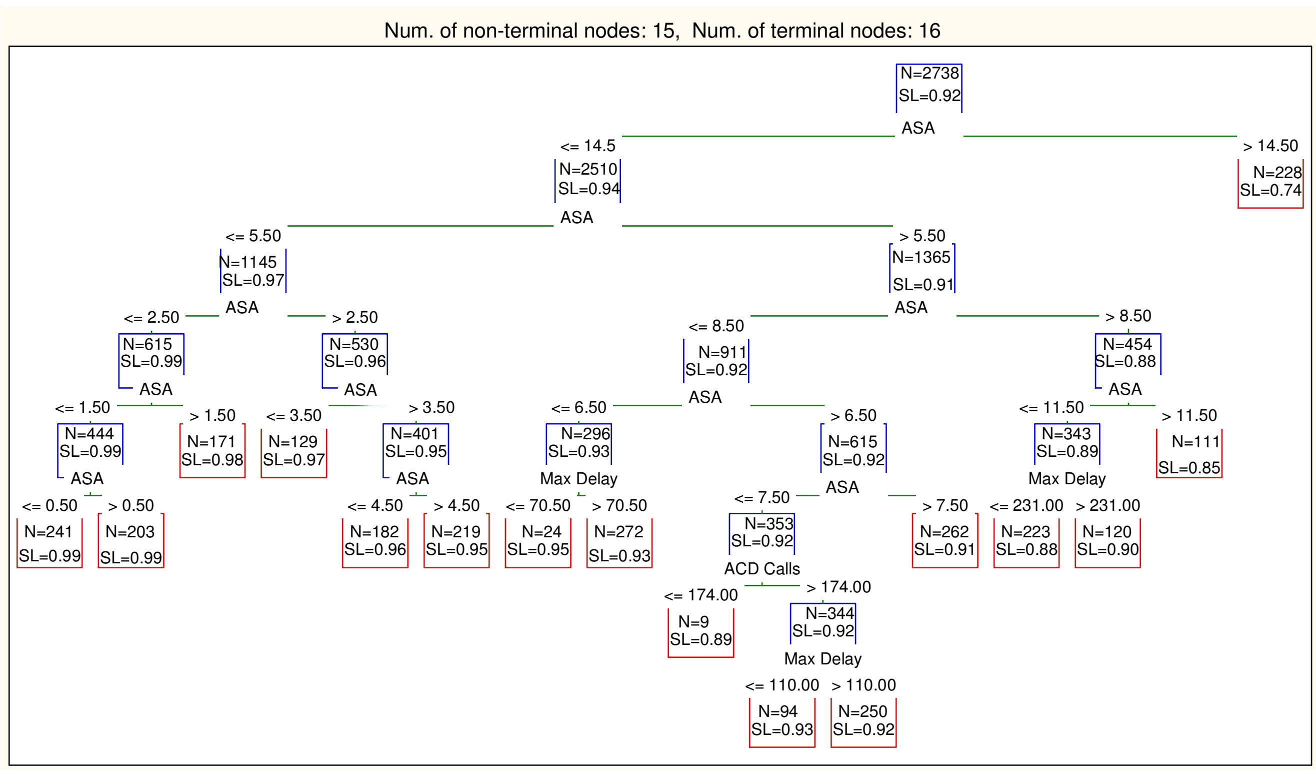

Figure 3: Decision Tree for Service Levels

An operational BI should be equipped with the capability of providing timely guidance regarding changes in the structure of operational parameters over time. A moving (sliding) time window of fixed length as used here is a reasonable first step in creating that capability, but it clearly leaves much unanswered regarding the appropriate characteristics of a moving time window.

Moving window techniques are useful in estimating time-varying model parameters and to construct adaptive responses assuming stationarity (stability of mean and variance) to hold only locally in time (Dahlhaus 1997).

Determination of the length of the time window requires compromise, since a long time window results in a small variance at the expense of a possibly large bias (*i.e.*, the series may include non-stationary features). On the other hand, separating quasi-deterministic effects (such as cycles) from stochastic variations is difficult with a short series.

Clearly the important question is how to detect a change in the structure. In a situation involving multiple time series such as a call center, the auto- and cross-correlation structure of those series can serve as a basis for judging an appropriate window length by noting the points at which predictive accuracy is lost (*e.g.,* significance of correlations at a given lag). But this approach depends to a certain extent on the degree of stationarity of the variance for both individual series (autocorrelation structure) and for the set of series (cross-correlation structure). If the change in volatility of an individual series is gradual and recurring, and its cross-correlations with other series are likewise stationary, a time window of a fixed size may suffice. However, if the change in volatility of the series is abrupt (*e.g.* shifts) and non-recurring, or if both types of change occur, the size of the time window would have to adapt to the speed of change.

In our call center circumstances change over time, and we want to know the effects of those changes, making recent data preferable. There is always some amount of natural instability in service levels due to changes over time in call center representatives, customers, and changing policies. However, we want enough data to offer a complete picture. If we operationalize a sliding window that includes too much data from previous years, than we are sampling from heterogeneous populations that are likely biased by data that does not represent changes due to the recent reallocation of call center resources. A good size to start with may be twice the length of the report timeframe. So if reports are weekly one may want to start with a window that is two weeks long.

Figure 3 shows the decision tree resulting from our data. The interpretation of this decision tree is straightforward. Blue boxes designate decision nodes and red boxes designate terminal nodes. At each node the mean service level (SL) and number of observations (N) meeting the service level are given. Mean values encompass all nodes below the given branch in the tree. The connecting branches provide the decision variable and corresponding cut-off values. For example, the topmost node has a mean service level of 0.92, this is the average for the whole tree since it encompasses all the nodes. However, for observations with an average speed of answer (first decision criteria) greater than 14.5 seconds the mean service level falls to 0.74. This tree is associated with74% of total variation in service levels. Statistica provides the mean square error (MSE) as a measure of accuracy with predictive decision trees. Traditional prediction methods, for example ordinary least squares regression, employ R^2, the coefficient of determination (proportion of total variation associated by the model), as a measure of accuracy. While not generally associated with decision trees, there exists no statistical obstacle to calculating R^2. Additionally, R^2 is more easily interpretable; clarifying how much variation in service levels is associated with the observed data, making clear how much variation in service levels the collected data explains.

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{Y} - \bar{Y})^2}{\sum_{i=1}^{n}(Y - \bar{Y})^2},$$

where $\hat{Y}$ is the predicted value, Y is the observed value, and $\bar{Y}$ is the mean of the observed values.

Closer review of the decision tree in **Figure 3** reveals that when average speed of answer exceeds 14 seconds, mean service levels drop to 74%. Mean service levels with average answer times less than 14 seconds are 94%.

DECISION-MAKING IMPLICATIONS

This proposed business intelligence system aids management decision-making in two ways: First, decision-makers can study the tree and isolate the variables affecting the response variable service level. Examining **Figure 3** shows that of the six variables entered into the analyses only five are included in the decision tree: handle time, speed of answer, abandons, maximum delay, and weekday. This provides managers with information regarding the importance of collected data. Second, a sliding window allows changes in resource allocations to be noted by call center managers.

Call volume is not included in the decision tree because it does not correlate with service level. The analysis suggests managers should focus on improving the treatment of existing calls instead of focusing on reducing call volume.

If we look at the economic rational choice process (Cyert et al. 1956), the final step in that process involves searching for problems to which an organization should focus their attention. Having already decided service levels are important, managers are able to focus their attention on the factors that clearly affect service level. This suggests that further study of each factor is necessary to determine the extent of the organization's influence over the factor. Average speed of answer is a dominant factor displayed in the decision tree in **Figure 3** above. However, the proposed process doesn't have the ability to perform a sub-analysis of the variable average speed of answer. If the organization wants to improve service levels they should learn what antecedents determine average speed of answer. This may involve collecting new data, or studying how efficiently the automatic call distribution system performs.

Figure 3 reveals that average speed of answer accounts for the predictions of over half the terminal nodes. Average speed of answer is also the only variable influencing the first three levels of the decision tree, and most of the fourth level. This demonstrates average speed of answer is very influential in determining service levels. The next most influential variables are abandons and maximum delay; they occupy positions at four decision nodes (two each). Managers should improve call center performance in those areas to provide the greatest gains in service level. While weekday and average handle.0 time are included in the decision tree they only apply to two decision nodes (non-terminal nodes) far down in the tree.

The decision tree can also provide predictions of future service levels based on current variable values. If current values for variables like average handle time, and average speed of answer stay approximately the same it is reasonable to predict that service levels will not vary much in the future. There are sources of variation in service levels that this decision tree does not account for, but they represent less than twenty-six percent of total variation.

Based on these results call center managers should first spend resources on reducing average speed of answer times to less than 14 seconds. This assures that mean service levels will be in the 90th percentile. Approximately 91% of calls have average speeds of answer less than 14 seconds, leaving close to 8% of calls with mean service levels of 74%. Within the 91% of calls with less than 14 second answer times 54% have answer times between 5.5 and 14.5 seconds, corresponding to mean service levels of 91%. While this sounds good, the call center strives for service levels at or above 96%, affording plenty of room for improvement. To achieve the 96% mark average speed of answer times will have to be less than or equal to 5.5 seconds.

CONCLUSION

The need for operational business intelligence is clear. Business intelligence provides opportunity for organizations to gain a competitive advantage by providing insight into daily processes that may not be fully understood by managers. The advantages of business intelligence are becoming well documented in both academic and professional literature. Call centers can provide clear competitive advantages for insurance companies. This is a clear call for research into ways to create and implement business intelligence systems utilizing data currently collected by organizations.

Our solution for achieving call center operational excellence provides call center managers knowledge regarding factors influencing service levels. Additionally, managers are provided a mechanism by which they can monitor the results of resource reallocations. The data analyzed shows that average speed of answer is the factor accounting for the greatest variation in service levels. The next step for management is to work towards ensuring answer times are low as possible. To achieve this more data may need to be collected regarding factors that influence answer times. While changes are being made modeling new data with decision trees provides a means for managers to continually monitor how each factor affects service levels. Currently the organization would like all service levels to be at or above 96%. Our analysis shows this is possibly for average speed of answer times under 5.5 seconds.

There exist several possible directions for future research. First, a program could be written to automate the decision tree construction using a variable (daily, monthly, etc.) moving window of data. This way we could observe how changes that affect speed of answer and delay times impact service levels. This is critical for managers to gauge the success of resource reallocation. Second, there are clearly additional outside factors affecting service levels that are not accounted for in the collected data. More research needs to be done to help isolate these factors. Additionally, research can be conducted to see if decision trees are the optimal choice for modeling collected data. It is very reasonable to assume we could have used regression. We chose decision trees because they are easy to interpret for managers that likely are not well trained in data analysis (i.e. low learning curve). It is important to remember that the system proposed here is primarily an exploratory system for call center managers. The system will identify factors that have the greatest impacts on service levels, possibly leading to a reallocation of resources, but ultimately it is the responsibility of a decision-maker to put these insights to good use.

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