1. Motivation

Customer churn is a major concern for most businesses in competitive industries. Understanding the factors that contribute to churn can help firms design better customer retention strategies. Keaveney (1995), in one of the early and influential studies of churn in the service industries, surveyed customers on reasons for switching services (broadly defined). The top two factors were core service failures (e.g. mistakes such as billing errors) and service encounter failures (e.g. “the doctor was curt”). Since then a variety of articles – mostly in the fields of marketing and operations – have addressed identifying the drivers of churn. While pricing, competition, and natural reasons (e.g. upgrading to a luxury brand with wealth increase) have all been demonstrated to be important, customer satisfaction and service quality (Graves et al. 1998) remain two critical factors that have received particular attention since businesses often have direct control on these. Rust et al. (1995) coined the term “return on quality” to reflect the importance of investing in service quality.

2. Research Question and Methodology

Surprisingly, empirical evidence demonstrating a causal relationship between specific service quality factors and churn have been sparse and weak. Gustafsson et al. (2005), while studying churn in telecommunications, did not find much of an effect of what is termed “reactional triggers” (which encompass core service failures as well as service encounter failures). A hypothesized reason for this is that perhaps such triggers take a longer time to affect churn than the data collected in the observational period. Further, most of the empirical work has focused on contractual settings where customer churn is directly observed by the firm (i.e. a user cancels a cellular account). Non-contractual settings on the other hand represent a large volume of business activity. Examples include hostelry and restaurants, where
individuals may transact less with a merchant than expected. Churn in such settings is “soft”, where a customer may still transact with a firm, but her share of wallet may have shifted in favor of competition.

In this research we are working with one of the largest logistics provider in the world to study the impact of service quality factors on churn. The setting is non-contractual as well. Customers always have multiple options for shipping packages and can easily switch shipping volumes in reaction to events. This study will therefore be one of the first to empirically examine service quality and churn in a non-contractual setting.

We adopt an exploratory pattern discovery approach for this problem given the large number (several hundred) of customer and service quality indicators that are known to or hypothesized to affect churn, interactions among which are also known to be important. For instance, it may be the case that most service quality factors do not impact churn but package delays coupled with location (e.g. availability of alternatives) may be an important combination rule. Rule discovery approaches are ideal for such problems since they do not seek any global model that will fit an entire data set but instead output any and all such (local) interactions of interest. We adopt a two-phased approach. In the first phase we assume the existence of a churn label provided by the group that leads data mining activities for the logistics company and learn churn segments. In phase two we learn churn segments by inductively determining unusually low volume segments rather than using the provided churn flag. The reason for doing so is to study the more general non-contractual setting where firms only observe volume and have to inductively determine whether there is churn. In such settings, methods to clearly label churn do not readily exist since much of the churn may only be observed as a drop in volume. However not all such drops may indicate churn. For instance, due to macroeconomic factors an entire industry segment may just be shipping less. Hence, data-driven methods that can intelligently flag such drops in volume are necessary.

3. Learning Churn Segments

We assume a database table of customers where each row represents one customer with the following attributes: customer attributes, service quality indicators for this customer over a pre-determined time horizon, and a single attribute indicating whether this customer has churned (or not). The churn attribute
could also be a continuous measure capturing the degree to which a customer has churned, as determined by revenue/volume data trends for instance. From such a database the approach described below will extract rules of the form:

Location = “San Diego”, Business Size = “Medium”, Missed Pickup Windows = “Low” \(\rightarrow\) Churn = 6%
(Expected churn 1 to 2%)

The methodology is based on the approach in Zhang, Padmanabhan and Tuzhilin (2004). In prior research this approach was applied to Web browsing data to learn segments where individual firms had higher or lower market share. Such rules are termed statistical quantitative rules (SQ rules) due to the fact that the consequent of these rules is a statistic computed from the segment satisfying the antecedent of the rule. Each such rule is output if the actual statistic for the rule is beyond a confidence interval computed using a non-parametric randomization methodology (Zhang, Padmanabhan and Tuzhilin, 2004). The form of these rules is as defined below.

**Definition SQ rule** (Zhang, Padmanabhan and Tuzhilin, 2004). Given (i) sets of attributes \(A\) and \(B\), (ii) a dataset \(D\) and (iii) a function \(f\) that computes a desired statistic of interest on any subset of data, an SQ rule is a rule of the form:

\[ X \Rightarrow f(D_X) = \text{statistic}, \text{support} = sup \]

where \(X\) is an itemset (conjunction of conditions) involving attributes in \(A\) only, \(D_X\) is the subset of \(D\) satisfying \(X\), the function \(f\) computes some statistic from the values of the \(B\) attributes in the subset \(D_X\), and support is the number of transactions in \(D\) satisfying \(X\).

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4. Information to Achieve Operational Excellence

The current generation of BI tools provides firms with a variety of informational tools, including visualization, dashboards, and analytics. BI systems provide timely access to information not just to IS professionals but to decision makers in all functional areas of an organization. However, despite their growing popularity BI capabilities still fall short of the “sense and respond” capabilities envisioned by IS academics (e.g. Nguyen et al. 2005). IS researchers have proposed architectures where such systems can help real-time and closed loop decision making by shortening the time between when events occur and the response by an organization.

Central to such sense and respond capabilities is the intelligence between transactional data and the response rules that might be in such a system. Our research proposes a design for this intelligence that can
bridge the gap between information and operational response, thereby taking an organization one step closer to operational excellence. In our proposed system operational data will be analyzed on a continuous manner to detect churn segments as they emerge. The BI dashboard of the COO will highlight emerging churn segments, prompting human intervention to develop tactical rules to diagnose and respond to the emerging threats. In the case of churn such intervention is likely to involve both operations as well as marketing activities (e.g. provide a gift card or a free shipping voucher from the organization the next time a package is being delivered and determine the reason for the sub-par operational problems that prompted the possible churn). Such a rule will then be integrated into operational systems that inform service representatives as they interact with clients.

We are in the final stages of obtaining a large data set that has highly granular information on service level indicators at a customer level coupled with time series data on transaction volume and churn. We will present preliminary results from the analysis at the conference.

References:


