A Guide to Season Ticket Holder Management

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Over the past year, we have been engaged in a variety of efforts centered in the sports marketing space. We publish a blog that comments on newsworthy topics (e.g. The Ed O’Bannon case or the Washington Redskins controversy) and we have developed two sports analytics oriented courses that are taught at Emory University.

In the next stage of our evolution, we are launching a series that we are calling Academia Meets Practice (AMP). The goal of the series is to present concepts, ideas and techniques that may be useful to key decision makers at sports organizations and students aspiring to careers in sports marketing. In general, the focus will be on methods for using data to improve marketing and business decisions. Over the last decade, there has been explosive growth in the field of marketing analytics. Given the nature and amount of customer data they possess, sports organizations are in many ways well positioned to leverage these techniques.

The purpose of this particular article is to present a structure for Customer Relationship Management (CRM) in the sports industry. Fan management has much in common with customer management in traditional marketing contexts, but there are a few unique aspects that create special challenges for sports marketers. In this document we review these challenges and discuss potential solutions. Our goals for this article include:

GOALS

- Establish the value of using Customer Lifetime Value as the underlying objective of season ticket buyer management.
- Introduce the basic concepts needed for developing a statistically-based decision-support system focused on season ticket holder management. Issues covered include modeling customer acquisition, customer retention, quantity decisions and migration between ticket quality levels.
- Highlight the importance of considering customer expectations in season ticket holder management. We also provide some preliminary insights into how the analyst can include “expectations” in statistical models of customer behavior.
• Discuss the complexities in dealing with ticket prices in a decision-support system. This discussion highlights various sources of information that may be used to develop a ticket quality index.

• Development of a framework that may be used to create / calculate dynamically optimal season ticket management policies.

In terms of organizational structure, we begin with a discussion of the appropriate CRM objective for sports franchises. The specification of an objective is an important, but frequently skipped, step in the design of CRM systems.

We then discuss retention modeling. While season ticket holder retention is just one of many important fan decisions, the retention decision is likely at the heart of any relationship marketing decision-support system.

Following the discussion of retention, we focus on how teams provide value to fans and how the structure of this “value” may lead to complex, dynamic decision-making on the part of fans. We also briefly discuss modeling techniques for considering decisions related to ticket quality, ticket quantity and package size.

Finally, the paper also includes material related to the conversion of customer response model results to marketing policies. This is an important but challenging topic as it requires a holistic view of the organization, marketing insights and sophisticated analysis tools.

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1. Fan Management Objectives

Sports franchises operate in an environment where it is increasingly possible to track multiple elements of an individual customer’s behavior. For example, season ticket contracts allow tracking of year over year retention, and bar codes allow tracking of ticket and concession usage. This type of detailed customer retention and revenue data makes it possible for sports franchises to use customer-focused metrics such as Customer Lifetime Value (CLV) and Customer Equity (CE) as primary marketing goals.

CLV is a core CRM metric that attempts to put a dollar value on a firm’s customer relationship assets. The idea behind CLV is that individual customers can be viewed in terms of the value or profit that they will contribute to the firm over some time period. For example, a customer that purchases a full MLB season ticket package (81 games) for two $100 tickets would provide a baseball team with $16,200 in revenue per season. If that customer was retained for 10 years, the customer’s lifetime revenue value would be $162,000 (assuming no inflation or discounting). If the customer was only retained for 5 years this lifetime revenue drops to $81,000.

While the previous example is obvious, there is a critical point to be made in regards to retention rates. Retention rates are much like compound interest as the impact of small changes becomes large over time. If a team has a retention rate of 95% per year the probability that a customer will last 10 years is 60%. In contrast, if the retention rate is 90% the probability of a customer being retained for 10 years drops to just 35%. Given that teams have high fixed but low marginal costs of serving a customer this means that small changes in retention rates can greatly impact profits.

It is instructive to express CLV in equation form. A simple formula for CLV is given in equation (1).

\[
CLV = \sum_{t=0}^{T} \Pr(Retention_t) \times (Revenue_t - Cost_t)
\]

In this formula \(\Pr(Retention_t)\) is the probability that the customer is retained in period \(t\), \(Revenue_t\) is the revenue produced by the customer in period \(t\), \(Cost_t\) is the cost to serve the customer in period \(t\), and \(T\) is the number of periods used for the CLV calculation. The basic CLV calculation can be extended to include additional factors such as inflation or discounting. The equation highlights the role of retention in the value of customer assets. \textit{In words, the equation just says that lifetime value is the sum of expected...}


profits generated from a specific customer over time. A critical insight is that the probability of retention is an incredibly important element of customer value.

However, the structure of the CLV equation as written in equation (1) should give sports marketing executives pause. The issue is that the equation is written without regard to marketing or team decisions. **If CLV is not a function of marketing the implication is that relationship marketing doesn’t drive customer decisions.** Below we rewrite the equation to make explicit that retention, revenue and costs may be a function of team marketing decisions at time t, $M_t$.

\[
CLV = \sum_{t=0}^{T} \Pr(Retention_t(M_t)) \times (Revenue_t(M_t) - Cost_t(M_t))
\]

For the purposes of this document, we take a very broad view of what constitutes “marketing.” In particular, a controversial issue is how to treat team quality. Our view is that team decisions related to payroll and roster construction should ultimately be viewed in terms of marketing consequences. This statement may be provocative as purists may believe that winning should be the ultimate goal and marketing and revenue generation are more appropriately viewed as supporting activities.

However, there is a strong case to be made for considering team payroll and roster decisions as marketing activities. From a consumer decision-making perspective, winning and losing are likely the main drivers of fan interest (in the near term). Winning rates are an interesting variable from a business perspective, in that sports teams actually have an objective and observable measure of quality. Given the established correlations between both payroll and winning, and winning and attendance, investments in team quality through payroll represent a direct means for driving attendance.

Investment in payroll and winning also has a longer term benefit. In our studies of brand equity in professional and college sports, we have consistently found that the key to creating a valuable, loyalty-inducing brand is winning championships. The implication of this finding is that investments in payroll and the pursuit of championships are often investments in brand equity and fan loyalty.

Writing the equation for Customer Lifetime Value as a function of marketing is useful as it makes explicit that the role of marketing (and payroll decisions) is to increase the value of customer assets. A frequent mistake in the field of CRM is to simply treat CLV as a fixed quantity that may be used to segment customers into groupings that vary based on expected CLV. This is problematic because it implicitly assumes that CLV is independent of marketing decisions. In the sports context, this is a particularly bad
assumption as investments in team quality (payroll) are obviously linked to season ticket holder retention and willingness to pay.

One final point before we move on to the key principles for this section. We have not placed much emphasis on data integration issues. This may be a significant issue in CRM. For example, in the preceding discussion we did not consider the possible complexities in measuring customer revenues. Revenues can include tickets, parking, merchandise, concessions, and potentially many other factors. As these revenues are collected through different channels it may be difficult to obtain a clear picture of individual level revenues. We do not consider these data integration issues in this note.

**Key Principles**

- The first step in customer management should be to set a clear objective. The objective we advocate is to maximize the lifetime value of current and prospective customers.

- Customer Lifetime Value (CLV) should be viewed as a function of marketing decisions. When this is the case, the marketing function becomes more accountable and goal-oriented. The key point is that the marketing department’s goals are related to the creation and management of valuable assets (customer relationships) rather than to short-term objectives.

- Marketing assets, such as customer relationships and brand equity, are a function of team payroll decisions and team performance. Team performance should not be viewed as unrelated to marketing policy.
2. Retention and Acquisition

In the last section, we made the point that customer retention is a key driver of customer lifetime value (CLV). The obvious implication is that a primary objective for teams should be to understand what drives retention decisions. When this is accomplished then teams can better invest in marketing programs or customer specific interventions.

Understanding the drivers of retention is best accomplished through the development of predictive models of season ticket holder retention. Perhaps the simplest decision to be modeled is whether or not an individual customer will choose to renew his / her season tickets. We will forgo consideration of ticket quality or ticket quantity for now.

We can begin with a simple equation along the lines of the following:

\[
\text{Pr(Retention)} = f(\text{something?})
\]

In words, this equation says that the probability (Pr) of renewal is a function (f) of something. The something is where things get interesting. In general, we might think that the “something” will include things about the team, the customer and the marketing decisions of the organization. From a conceptual perspective, the “something” should be focused on the decisions that the club can make. This is important because the end goal of this type of work needs to be some type of decision-support system that allows the club to understand how its decisions impact its customers’ decisions. From a practical perspective, CRM systems and predictive analytics are often constrained by data availability. In other words, we often predict based on the data we have rather than the data we truly want.

**Dependent Variable.** For the analysis of retention, the dependent variable (the “what” we want to predict) is the Yes / No renewal decision made by season ticket holders. This decision may be treated as a binary outcome. Another Yes / No decision that is common in CRM applications is customer acquisition. We briefly comment on modeling this decision later in this section.

**Explanatory Variables.** The second type of variable that we need to consider is explanatory variables. As the name suggests these are the variables that we will use to explain the yes / no decision. These explanatory variables can come from a variety of sources and may be under the control of different decision makers. For instance, one team-level factor that may impact customer retention is team success. Fans clearly are
more interested in supporting winning teams than losing teams. Winning rates are an interesting variable to include in a marketing decision support system since team quality is probably beyond the purview of the marketing department. Other potential team level factors to include in a retention model are given below.

Team-Level Variables:

- Last season’s winning percentage
- Last season’s post season results
- Previous season finish (place or games back)
- Team payroll (to control for star power)
- Number of all-stars
- Any other team factors that affect customer interest or expectations for next season

At the core of most CRM systems is individual level customer data. Across many industries a consistent finding is that past loyalty is the best predictor of future loyalty. Many categories use recency (time since last purchase), frequency (the number of purchases) and monetary value (the cumulative amount spent) as core predictors of future customer loyalty. These RFM measures are derived from customer transaction history data. In addition to basic transaction history measures, teams may find it useful to model retention as a function of other customer data such as distance to stadium or amount spent on concessions. The relevant customer data is something of an empirical question. Teams should start broadly and use statistical techniques to determine what customer traits are useful for predicting future purchases.

Customer-Level Factors:

- Time as a season ticket holder
- Attendance frequency (if available)
- Distance to the stadium / arena
- Transaction history measures (ticket prices paid, etc.)
- Customer initiated interactions with customer service

Another type of variable that needs to be considered is “marketing decisions.” These are the variables over which the marketing department has direct control. These are also the critical variables for understanding the pay-off to specific marketing programs. These
marketing decision variables include the traditional elements of the marketing mix such as prices, discounts, advertising and customer contacts.

Marketing Decisions:

- Price
- Customer contacts (frequency and type)
- Promotions
- Discounts

The preceding list is in no way meant to be exhaustive. The appropriate variables to collect and study are something of an empirical question. Teams should weigh the cost of data collection and experiment with variables to ascertain which are the most predictive.

**Modeling Customer Retention.**

The move from data collection to analysis is often a significant challenge. Many organizations still exist in the realm of descriptive statistics or simple cross-tab type relationships. For example, a team might do a simple comparison of retention rates as a function of average prices in each section. These types of relationships are easily visualized and can be of significant value. However, as the preceding discussion about data suggests, there may be a significant number of factors that affect decisions. It is for this reason that we advocate for the use of statistical models (that can separate out multiple effects) to understand the relationships between factors.

The fact that our decision is a yes or no choice rather than a quantity may complicate the modeling process. The problem is that the standard linear regression model is designed to predict continuous variables (like income) rather than dichotomous outcomes (such as yes or no renewal decisions). Specifically, the main objection to a linear regression model is that the model predictions are not constrained to be between zero and one (remember we are trying to predict a probability).

For example, we might wish to predict the probability of a purchase (or renewal) based on price, years as a customer and the team’s winning percentage last season. Equation (3) listed below illustrates how these factors might look in a linear regression model.

\[
Pr(Buy = 1) = \beta_0 + \beta_p Price + \beta_{yrs} Years + \beta_{Win}\% + \cdots
\]
For purposes of illustration, let’s say that the above equation was estimated using data on season ticket holder behavior and the resulting coefficients are given in equation (4).

\[
Pr(Buy = 1) = 0.4 - 0.01 Price + 0.02 Years + 1.2 Win\%
\]

Equation (4) may be viewed as both an analysis of customer behavior and also as a decision support tool. For example, the coefficients suggest that a $10 increase in price reduces retention by 10% while an increase of winning percentage of 10% increases retention by 12%. This type of information can begin to provide insight into how management decisions impact fan response.

An alternative to the linear probability model is logistic regression. Logistic regression shares some similarities with linear regression, but there are important differences. In terms of similarities, the logistic regression can also predict the likelihood of an event as a function of a set of explanatory variables. Just as in the preceding example, retention could be predicted as a function of price, years of purchase and winning percentage.

The primary benefit of logistic regression is that this model constrains the estimated probabilities to between 0 and 1. This makes the model’s predictions more interpretable and results in more intuitive “scores” for each customer in the database. However, the logistic regression model does involve some additional complexity. First, the logistic regression requires specialized software such as SAS, R or SPSS. Second, interpretation of coefficients is not as straight-forward. Equation (5) presents the expression required to predict probabilities based on estimates from a logistic regression.

\[
Pr(Buy = 1) = \frac{\exp(\beta_0 + \beta_p Price + \beta_{yr} Years + \beta_{win} Win\% + \ldots)}{1 + \exp(\beta_0 + \beta_p Price + \beta_{yr} Years + \beta_{win} Win\% + \ldots)}
\]

**Customer Acquisition.** Thus far we have focused on retention or repeat buying. This is a yes or no decision: do I renew my tickets or do I allow my season tickets to lapse? Another yes/no decision made by customers is the initial decision to become a season ticket holder. Linear probability models or binary logistic models based on individual, team and marketing variables may also be used to analyze the drivers of customer acquisition.

There are a couple of items that separate retention and acquisition analysis. The primary issue is that in the case of acquisition the firm is unlikely to have a great deal of customer specific data. A particularly important type of acquisition study is the analysis of acquisition campaigns. For example, a team might use direct mail to offer an introductory customer discount to a set of prospects. Logistic regression could be used to
determine how multiple factors such as offered discount, distance from stadium or arena or demographics based on zip code impact acceptance of an offer. This type of information could be used to refine future direct marketing efforts.

**Key Principles**

- The development of a statistical model of retention has multiple benefits. The modeling exercise reveals what factors have a significant impact on consumer decision making and what factors do not drive customer behavior. For example, the model might reveal that concession prices impact retention while parking prices do not.
- In addition, the relationship between team actions and fan decisions becomes quantifiable. For example, a model could reveal that when winning percentage increase by 1% that retention increases by 2%.
- Retention (acquisition) analysis may be accomplished using relatively simple tools such as linear regression performed in an excel spreadsheet or with slightly more complicated procedures such as logistic regression.
3. Analyzing Fan Behavior: Extensions

As noted above, season ticket-holder behavior is more complicated than simple yes or no renewal decisions. Season ticket holders also decide on ticket quality, size of package and number of tickets per game. Data is also increasingly available about attendance decisions and reselling behavior at the level of individual games. In this section we briefly discuss the analyses of these decisions.

**Ticket Quality.** Most teams sell multiple price points of tickets. For example, if an area has three sections, defined in terms of quality (A, B and C), it may be of interest to model the selection of ticket quality tier. One approach to doing so could be an ordered logistic regression model. This is similar to the binary logistic regression model used for analyzing retention or initial buying decisions but the ordered logistic model allows for multiple levels of a decision.

Given a set of customer characteristics, team characteristics and marketing decisions, it becomes possible to predict the probability that a customer will purchase in section A, B or C. However, the standard ordered probability model would likely need to be generalized in order to model ticket quality. The critical issue is that multiple prices may impact the section decision. For example in a 3 section arena where section A is the premium section and section C is the least desirable the customer is confronted by three distinct prices. The probability of selecting a seat in section A may be a function of the prices in section A and section B only since customers interested in premium seats may not even consider seats in section C.

It is also possible that it may not be possible for fans to migrate upwards to higher quality tickets. If sections made up of higher quality tickets are usually sold out then a naïve model would underestimate the desire of a fan to upgrade. In statistical terms, this is known as censoring. For instance, during a cursory look at season ticket holder decisions, we might find that customers who sit at the 40 yard line almost never migrate to seats at the 50 yard line. An unsophisticated conclusion would be that these customers are not interested in upgrading their seats. The problem is that higher quality seats may not be available since seats on the 50 yard line are always sold out. In technical terms a statistician would say the desire for upward quality transitions is censored or unobserved due to capacity constraints. From a managerial standpoint, this type of situation may obscure the true value of premium seats and may mistakenly lead analysts to conclude that customer migration is a minor issue.
Modeling ticket quality decisions is an extremely important task. Given the level of loyalty fans have for their preferred teams, season ticket holder relationships have the potential to last for multiple decades. With customer lifetimes of this duration, it becomes important to consider more general customer lifecycle issues such as general movements towards higher quality seats.

**Ticket Quantity.** Another customer decision that may be analyzed using an ordered probability modeled is ticket package size. Teams commonly offer complete season, half season and other smaller season ticket packages. The natural size ordering of these categories of packages means that an ordered probability model is again an appropriate tool.

For example, if a team offered full, half, and quarter season packages, the ordered probability model would be specified to predict the likelihood that a given customer would select each level. As in the case of ticket quality, care would need to be taken in terms of model specification. In particular, the manner by which price was included in the model would need to be handled with care.

**Purchase Timing.** In our discussion of renewal decisions, we basically assume that customer’s decisions are driven by variables that remain constant. This may be a significant limitation if customer’s decisions are a function of variables that change over time. For example, the probability of a renewal might change over the months of the off-season as a team makes roster moves.

The engineering and medical fields have developed models for analyzing time until failure or until death. These are called “hazard” models in engineering or “survival” models in bio-statistics. The marketing field has begun to utilize these techniques to predict when customer might make a purchase or end a relationship with a firm. As in standard regression models, these techniques can include explanatory variables. An example of when these models might be useful would be as a tool for analyzing the impact of free agent signings on season ticket renewals.

**Fan Expenditures.** Teams may also have an interest in modeling total expenditures or contribution. Sports fans tend to do a great deal of add-on spending beyond tickets. Parking, concessions, and souvenirs may all represent significant contributors to the value of a customer. Total expenditures is easily modeled using linear regression. Standard regression models are appropriate since expenditures is a continuous variable.
It may also be useful to translate expenditures into margin or contribution. While the marginal costs associated with a fan sitting in a seat are very low, the costs associated with food or merchandise will be much higher. Therefore, it may be of great value to convert revenues into margins since this would allow the CLV calculations to directly speak to profitability. This is likely a simple task as multiplying category revenues (concessions, tickets, etc…) by average category margins is probably sufficient. However, while the analytical challenges may be simple, the integration of revenues from different revenue centers may be a significant challenge.

**Game Attendance Decisions.** It may also be of interest to model game-level decisions, such as whether a season ticket holder attends the game or sells the ticket on the secondary market. At the level of the individual game, the analyst may use logistic regression. The explanatory variables for this analysis might include opponent team performance at that point in the season, recent performance trends, variables related to the opponent, time of day, day of the week, weather and numerous other factors.

A game level analysis might be useful for a variety of business issues. For example, understanding the impact of opponent characteristics, time of day, or whether the game is played on a weekend could inform efforts to create a variable pricing schedule. Understanding the relationship between customer characteristics and transaction history variables might provide a basis for an early warning system for identifying at risk customers.

Season level attendance could also be analyzed using a class of procedures known as count models. A count model could be used to predict the number of missed games based on individual customer factors such as ticket tier, distance to the stadium and years as a season ticket holder. Customers that show significant deviations from the model predictions would likely be very loyal or very much at risk.

**Key Principles**

- While retention modeling is probably the core of customer analysis, there are many additional decisions that should be analyzed.
- Continuous outcomes such as total expenditure may be modeled using standard linear regression, variables with an ordered structure such as ticket quality can be analyzed using ordered probability models and purchase timing may be modeled...
using hazard models. The point is that consumers make multiple types of
decisions and statistical techniques exist for each possible type of decision.

- The value of modeling decisions beyond retention may be related to better prediction of CLV or as input to decision tools related to identifying at risk customers.

- Many of the techniques identified above require specialized software and a high-
level of statistics training.
4. Ticket Quality and Pricing

A common challenge in modeling demand for sports is a difficulty in estimating the relationship between price and demand. Game or section level models of demand as a function of price will commonly yield positive price parameters. For example, if the best seats are priced at $200 and these seats all sell out, while the most distant seats are priced at $10 and often do not sell out, a naïve statistical model would suggest that demand increases when prices are higher. The fundamental issue is that the seats within a stadium or arena are of very different qualities. It is necessary to control for the heterogeneous nature of inventory quality when modeling the relationship between price and demand.

One approach advocated in the academic literature is to use the distance from some focal point in the facility (home plate, mid-court, etc…). But this is often a flawed method. The figure below shows a seating diagram for the University of Illinois’ Assembly Hall. The circular shape of the seating area highlights the potential issue with using distance as the quality metric. The distance to center court from for a given row in Section 7 will be the same as a seat in Section 44 but it is doubtful that many fans would choose to sit behind the basket if given a choice.
Thankfully, current trends are making available significant amounts of data that may be used to create a meaningful ticket quality index. In terms of internal data, teams likely possess an historical record that may be of value. Within a season, it is possible to look at which seats sell first and which seats within a section sell last or remain unsold. The growing secondary market contains a significant amount of information that may be used to develop a ticket quality index. The most obvious data that can be extracted from the secondary market is true reservation prices for each specific seat. In addition to providing market prices for different seats, the secondary market can also provide information on the timing of demand. Primary research methods such as conjoint analysis could be employed to understand seat quality differences.

A seat quality index would be useful for estimating models of consumer demand. Rather than use prices directly, it would be useful to create a dollar per quality index for sections of similar seats.

The appropriate incorporation of price into CRM models varies based on the objective of the analysis. In a simple binary renewal versus lapsed model, it may be sufficient to include last season’s price and any price changes. However, the analyst should understand that this approach includes an implicit assumption that customers do not consider shifting up or down in terms of seat quality.

If the analyst wishes to include migration between quality (and quantity) levels, slightly more sophisticated modeling techniques such as ordered logistic or probit models are needed. Assuming that migrations tend to be to adjacent quality tiers then quality adjusted prices and price changes for three classes of seats need to be included in the model. This type of problem would require an ordered or multinomial probability model.

**Key Principles**

- Incorporation of prices into season ticket and single game ticket sales is not a straight-forward issue. The variation in quality of tickets across a stadium or arena means that price elasticity cannot be properly assessed without an adjustment for ticket quality.
- Both internal and external data may be used to create an index of seat quality. Internal data sources might include the order in which customers select seats within a price point. The growing secondary market provides market level willingness to spend on each seat.
• Development of a seat quality index based on secondary market information requires statistical models that control for factors such as time of day or opponent. These analyses therefore can aid in the creation of variable and dynamic pricing systems.
5. Customer Expectations

A critical aspect of consumer decision-making in the season ticket context is the role of expectations. Considering consumer expectations introduces a great deal of complexity into the analysis but this cost may be worth paying. The potential value in directly modeling consumer expectations is that the link between on-field decisions and consumer behavior is solidified and made explicit.

Expectations may take multiple forms. For this note we will consider two distinct types of expectations. The more common of these is expectations of next season quality. Expectations of next season’s quality are likely to be a function of last year’s performance, any upwards or downwards trends from the previous season and the club’s off-season additions or subtractions. For example, in response to the selection of Johnny Manziel in the NFL draft, ESPN reported that the Cleveland Browns sold more than 2,300 season tickets within 24 hours of the pick. ESPN also reported that the Cavaliers basically sold out of season tickets within 8 hours of LeBron James’ announcement that he would return to Cleveland.

For a few teams, fans may have expectations regarding future scarcity. For example, teams like the Packers or Steelers may endure losing seasons without loss of season ticket holders because fans expect long waiting lists and limited access to re-subscribe. The Packers report that the waiting list for season tickets “has more than 81,000 names” and that the average wait for tickets is 30 years. If ticket quality is also a function of time as a season ticket holder, fans may also have expectations regarding access to premium tickets.

Modeling expectations is a tricky endeavor because expectations are not directly observable. A variety of options are possible. One simple approach is to develop a stand-alone performance forecasting model. Forecasted performance would then enter directly as a covariate in the customer utility function.

A more complicated approach would be to estimate the model under the assumption that customers act as dynamic optimizers. In this model, the customer’s sequence of decisions is analyzed rather than just the immediate “one” season decision. These types of *dynamic programming models of customer behavior* require a significant amount of specialized knowledge and software.
Key Principles

- Consumers, in general, and season ticket customers, in particular, often make decisions based on expectations and other forward looking factors. To truly understand season ticket holder behavior requires techniques that can incorporate these expectations.
- The types of expectations that are relevant will vary across clubs. Expectations of next season performance are likely a factor for most teams. Expectations of future season ticket scarcity are more applicable to teams with frequent capacity constraints.
- Techniques for modeling forward-looking behavior can range from including a simple forecast of next season performance in a linear regression to developing an explicitly dynamic statistical model that attempts to replicate the forward-looking nature of consumer decision making.
- Consumer expectations are obviously driven by off-season player moves. Explicit modeling and inclusion of expectations in customer retention models therefore helps to connect player decisions to marketing outcomes.
6. Optimal Customer Relationship Marketing

We now shift attention to the development of marketing and team strategy policies. The figure below shows a simplified segmentation structure. The circles or nodes on the figure represent four customer segments that are defined in terms of current and past purchasing decisions.

The first segment is labeled “Prospect” and includes identifiable consumers that have not made a purchase. In the case of the season ticket holders prospects could be defined in a variety of ways. They might be limited to consumers that have made inquiries but not made purchases, or the definition might be extended to include customers that have only purchased single game tickets. The second segment is labeled “New Customer” and includes first time season ticket purchasers. The third segment is labeled “Repeat Customer” and is comprised of customers that have purchased in at least two subsequent periods. The fourth segment contains customers that have previously purchased but have failed to renew. This segment is labeled “Lapsed Customer.”

The arcs connecting the segments represent transitions between segments that occur based on the annual decision of whether or not to purchase season tickets. For example, a prospect may either make a purchase and transition to the first time buyer segment or not make a purchase and remain in the prospect segment. New customers may renew and become repeat customers, or fail to renew and become lapsed customers. Repeat customers either renew and remain repeaters or become lapsed customers.
While this is a very simplified segmentation scheme, it highlights the team’s CRM problem. Obviously, the key to maximizing value is to move customers from the non-buying customer segments into the buying customer segments.

The arcs (transitions) should be viewed in terms of probabilities. In the specific and limited segmentation structure illustrated in the diagram, the probabilities would be derived from the customer acquisition and retention models discussed previously. A critical point in this framework is that these probabilities are based on individual customer traits, team performance and marketing decisions. The implication is that marketing becomes at least partially responsible for the value of a team’s customer relationship assets.

The final step in the CRM process is therefore how to develop marketing policies (and possibly team spending policies) in order to maximize the value of current and future season ticket holders. This might be accomplished through Monte Carlo simulations of different marketing or team scenarios or through the application of dynamic optimization techniques. For both of these techniques, the types of models of consumer response and revenues we have discussed would be the primary inputs.

**Key Principles**

- A critical element of CRM is to define customer segments in terms of customer profitability. The goal of relationship marketing then becomes to drive customers into higher profitability segments.
- The retention and acquisition models discussed earlier should be designed to predict the transitions between these segments or customer states.
- Optimization procedures may be applied to determine the marketing and team policies that maximize the team’s customer equity.
- Optimization of customer management is a complex analytical problem. Significant data and statistical expertise is needed to model customer behavior. Dynamic optimization requires advanced skills in the area of applied mathematics or operations research.
7. Final Comments

Our overarching goal in this note was to provide a structure for how teams (or more generally any firm that operates in a capacity constrained environment) might approach CRM. Along the way we have provided some guidance in terms of how various types of consumer’s decisions might be modeled, and how these models can be combined to develop improved marketing policies. The elevator version of the document would involve the following three points:

- Season ticket holders are valuable economic assets. Teams should view the customers as assets and manage these customers in a manner that maximizes the long-term value of each customer.
- Trends in computing and information technology have progressed to the point where it is increasingly possible for teams to collect the needed data to build sophisticated models of a variety of consumer behaviors.
- Data, statistical models, and optimization techniques may be combined to create optimal marketing policies. In other industries it has been found that using dynamic optimization to create individual level relationship marketing strategies (such as targeted discounts or direct interventions) can result in 20% to 30% growth in profitability.

One thing that we have tried NOT to do in this document is to overwhelm the audience with technical detail. This was done for two reasons. First, we wish to make this article (and future articles) accessible to a wide audience. As such, we have tried to keep a balance between relationship marketing philosophy and statistical directions. Second, managers in sports settings (and managers in just about any category) should be leery of a one-size-fits all CRM and analytics solution. In our experience, there is a great deal of need to customized modeling approaches and data collection across firms. For this reason, we think it is more useful to discuss general approaches to modeling and matching of techniques to problems rather than to go into detail.