Forecasting Customer Lifetime Value: A Statistical Approach

Erniel B. Barrios[a*] and Joseph Ryan G. Lansangan[b]

[a]*Professor, University of the Philippines, School of Statistics, Diliman, Quezon City 1101, Philippines*
[b]*Assistant Professor, University of the Philippines, School of Statistics, Diliman, Quezon City 1101, Philippines*

We propose a method of forecasting customer lifetime value using the customer usage database, sampling strategy, segmentation, modeling, and validation techniques in data mining. The highly heterogeneous customer database being mined will allow the inclusion of uncertainty components in the estimation of customer lifetime value. A hazard function model based on a truncated lifetime data of customers can provide adequate information to compute the value of the incentive to be offered and the length of the lock up period for the customer.

Keywords: data mining, customer lifetime value, customer relationship management, truncated data, hazard function model

1 Introduction

In a highly competitive sector, the cost of customer recruitment is generally higher than cost of promotions to retain them. It is important for marketing planners to develop strategies of initially attracting customers and engaging them to patronize the products in the long run. One common strategy used is to lock them up for a specific period to patronize the product with a minimum usage (e.g., loyalty cards, telecommunication, credit cards, etc.). The customer can only be motivated to enter into such a contract if attractive incentives are available. The value of the offer and the duration of the lock up period can be assessed based on lifetime profitability of the customer.

The dynamics of customer valuation expand with the growth of non-static data together with profile (possibly static) data. Most companies consider customer valuation by looking at customer behavior based on transaction, experience, perception, or opinion data. Ideas such as how likely, how much, how many, or how soon can be inferred from understanding a customer's behavior – how likely he/she will discontinue engagement, how much profit is expected, how many he/she will possibly influence, or what or how soon the next purchase is expected. This information is valuable input in customer relationship management. For example, a credit card company can waive annual dues provided that the customer can be expected to be profitable within the period. A subscriber of a telecommunication service can be offered incentives like equipment or discounts provided that patronage for specific duration is assured. Such is also true for privilege card for restaurants and shops, mileage card for airlines, and the like.

With the volume of data at hand, data mining techniques are commonly employed to extract the patterns useful to achieve the company objectives. Classification and/or clustering methods are used to identify "natural" groups based on data. Most methods draw on association rules to discover relations among different purchases and come up with likely "bundles" or "basket mix." Regression models are developed to identify possible factors of an event of interest (e.g., defaulting, acquisition, purchase, etc.). Companies take advantage of many statistical techniques that yield insightful information to their business strategies. As such, customer life cycle management remains among the priorities of most if not all consumer companies, having units such as in business intelligence (BI), customer relations/engagement (CR/CE), or market research (MR).

Customer lifetime value (CLV) modeling is at the core in customer life cycle management. Different approaches are carried out to understand the customer "importance" in relation to profitability. A "score" is calculated for each customer, reflecting "how much" a customer is worth or equivalently, how much the company should spend to retain the customer vis-à-vis acquiring a new one. Among the more common approaches are customer segmentation, modeling customer average revenue or return on investment (ROI), customer longevity (i.e., occupancy period, engagement measured through time and tenure), termination/churn rate, and acquisition/retention cost.

---

* Correspondence: Tel: +63 2 928 0881; Fax: +63 2 9280881. Email: ernielb@yahoo.com

We propose a methodology in the development of customer lifetime value models. Data mining techniques and statistical modeling procedures are presented in the development of CLV models. The methodology will require a database on customer usage assuming that transaction details are stored and readily available in its data warehouse (recording at a customer-level). Customer account details are also needed (e.g., sex, age, date when first purchase started, engagement duration, or tenure), and as to whether the customer is continuing (or active) or non-continuing (historic). As a metric of customer's worth, CLV scoring can be based on the customers' usage and/or patronage of the products/services. It is imperative for the company to assess its return on investment (ROI) on a particular customer, and alongside foresee the customer's engagement measured in terms of tenure with the company. We propose modeling strategies for average revenue and tenure per customer.

2   Customer Lifetime Value: Measures, Models and Uses

Customer Lifetime Value (CLV) is the current valuation of all future profits from the customer, estimated at the individual customer level, (Gupta & Lehmann, 2003). There are many other definitions of CLV producing various natural measures. From a supplier-oriented perspective, (Bauer et al., 2003) defined customer value as the customer's economic value to the company and proposed to use customer lifetime value in corporate valuation. Customer activities contributing to company income like up-selling, cross-selling, or referrals can benefit from using customer value as benchmark of profit computation and resource allocation. The CLV is an important element in corporate decision-making and decision points maybe chosen to optimize CLV, (Crowder et al., 2007). As noted by Rust et al. (2011), this encourages many companies to invest in customer databases that will support forecasting of CLV values. Consequently, such database and measures of CLV can also be used in modeling churn (Glady et al., 2009a) for the development of empirically supported marketing strategies. Subsequently, data mining became a very valuable tool towards the extraction of information from the database (see Khajvand et al, 2011, for details).

Customer relationship management is an important component of business intelligence. It provides an integrative framework in which marketing activation and customer activities collaborate to increase patronage. Venkatesan and Kumar (2004) noted that CLV can also be maximized within the framework that allows managers to maintain or improve customer relationships through marketing contacts across channels. They further suggest that CLV is a viable metric for customer selection and marketing resource allocation. Malthouse and Blattberg (2005) emphasized that firms can be more profitable if they identify the most profitable customers (with high CLV) and invest favorably large amount of marketing resources on them rather than in those with lower expected CLV. Dwyer (1989) noted the value of CLV in support of marketing decision-making. CLV and consumer behavior can be jointly featured in planning for optimal marketing mix that will lead to the improvement of long-term profitability.

Many frameworks were proposed in the measurement of customer lifetime value (CLV) as they are linked to other activities that stimulate corporate dynamics. Berger et al. (2006) proposed the chain of effects framework in the understanding of the influence of CLV on shareholder value. Just like in other frameworks, measurement of CLV is a major issue. They suggest that since CLV measurements are usually based on past data, elements of uncertainty should be incorporated in the models used to measure it, and that expectation rather than deterministic accounting measures should be employed. This approach, however, is constrained by the measurement of uncertainty.

Among the early proposal to measure CLV, Berger and Nasr (1998) used a series of mathematical models (diffusion theory) based on theory and on assumption grounded in customer behavior. Some of the possible applications of CLV from this process includes: relationship marketing, marketing and promotional resources allocation, assessment of the effect of marketing strategy in acquisition and retention rates, costs and tradeoff, and customer equity.

To maximize outcomes of certain marketing activities on CLV in a telecommunications company, Rosset et al. (2003) suggested the development of CLV model based on segments of the population of consumers, and model customer value and tenure separately before the integration to come up with CLV. As noted by Lee et al. (2006), valuation of customer based on financial indicators alone could be misleading since there are other latent factors that can potentially influence CLV. They further

highlighted that managing customer relationship by inputs (acquisition and retention) and outputs (revenues) for each customer can facilitate better prioritization of marketing investments by differentiating customers. Ryals and Knox (2005) suggested measuring risk-adjusted CLV and its impact on relationship marketing strategies and shareholder value.

The potential measurement errors in CLV posed a major limitation in modeling CLV. Decision tree, a nonparametric classification methodology, was used by Han et al. (2012) in segmentation (based on CLV) of telecom customers, since this method is known to be robust for measurement errors. To further mitigate the measurement error problem, Benoit and Van den Poel (2009) used quantile regression in modeling CLV of financial services customers. Some stochastic process models were also proposed in modeling CLV (see Ma et al. (2008) and Glady, et al., 2009b, for examples).

There are several works on the uses of CLV in marketing and strategic business decisions. Gupta et al. (2006) postulated that companies increasingly generate income by initiating and enhancing a sustainable relationship with the customers. Incentive planning using CLV was proposed by Reinartz and Kumar (2003) as a strategy to increase profitability of customers. Bose and Chen (2010) suggest that knowledge from CLV of mobile services customers could enable the alignment of marketing strategies to customer needs. Chan and Ip (2011) noted that forecasts of CLV are a viable tool in new product development. There are many other uses of measurements and models of CLV (for examples, see Wu & Li, 2011; Mikkonen, 2011; Kim et al., 2009).

3   A Statistical Approach in Forecasting Customer Lifetime Value

To measure customer lifetime value, two quantities are proposed: tenure and average revenue per customers (ARC). Tenure accounts for the uncertainty in activities of similar customers in the future while ARC will quantify the revenues generated from patronage activities among the customers in the past. ARC and tenure jointly determine the expected CLV of existing and forthcoming customers and can be used for strategic customer relationship planning.

While data for the population of customers are usually available in the database, its size could be a hindrance in efficient computing that can delay the generation of valuable information for decision-making. Data mining usually starts with sampling. Ideally, stratified sampling is used to ensure representation of various customer segments. The choice of stratification variables, (e..g, status of account, account type, tenure cuts, and so on) is crucial.

3.1   Tenure analysis

For tenure analysis, two different models can be developed-- one that used only tenure thru a survival model (i.e., hazard functions, see Eq. 1) for expected lifetime (EL), and the second that used a generalized regression model with (left and right) censoring to estimate end-of-lifetime (EOL) after current period. For the first model, hazard functions are fitted on the data set and on each of the pre-determined segments (e.g., customer's age group, gender, account type, etc.). The survival function $R(t)$ at time t, is defined as $1-F(t)$, where F is certain parametric distribution. The following hazard function model can be constructed:

$$T_t = \frac{F\left(x_t^{'}\beta\right)}{1-F\left(x_t^{'}\beta\right)} \tag{1}$$

The covariate x's may include measures of financial-related interactions with the customers, cumulative usage, and other individual transaction profiles. The link function F is usually logistic distribution, although log-normal or other skewed distributions may also be used. Hence, with tenure (in months) as the dependent variable and logistic link function, the following tenure model can be estimated:

$$T_t = \frac{1}{1+\exp-\left(X_t^{'}\beta\right)} \tag{2}$$

The model is used in predicting tenure of current accounts with transactional data accumulated until the current date (with the frequency of data aggregation depending on the intended requirements on the usage of the forecasts). The survival function is illustrated in Figure 1.

Figure 1. Probability of Survival Function
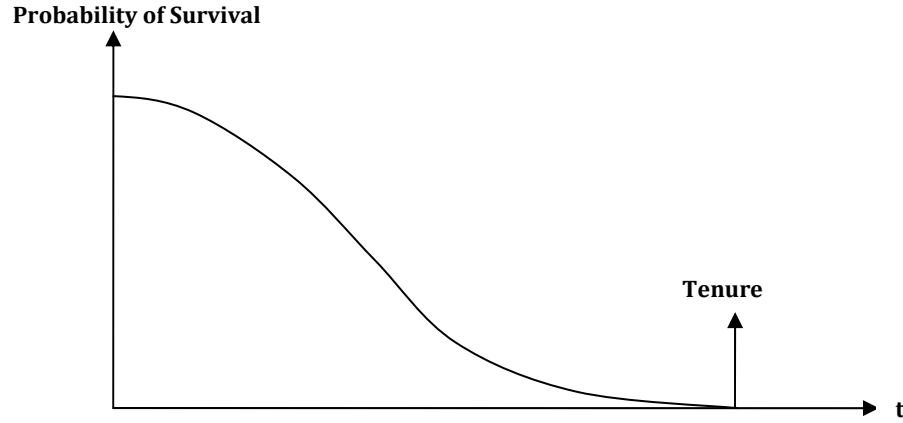
Under the second model, transactional data should be accumulated over a recent period. These will be used as the covariates along with other customer's profile data. The total tenure of estimated customer lifetime is then computed by optimizing the tenure in Eq. 2. The customer lifetime is obtained from the height when equation (2) approaches the asymptotes (see Figure 2 for the illustration).

Figure 2. Customer Lifetime Model
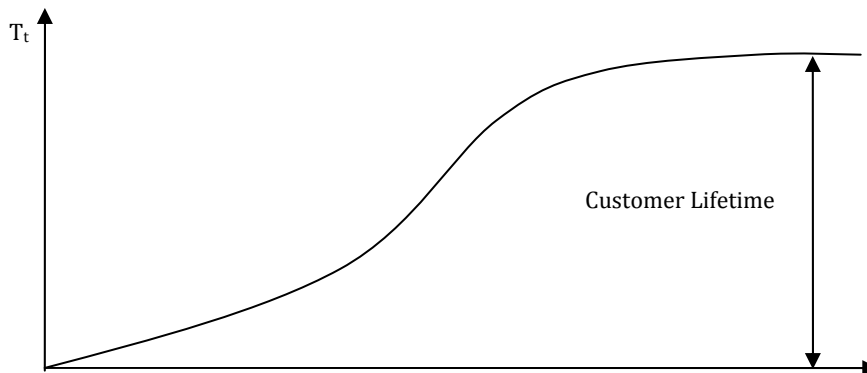
3.2   Average revenue analysis

For the average revenue analysis, a seemingly unrelated regression (SUR) model (i.e., structural equations model) is used to build forecasts of average revenue per customer (ARC) based on the frequency, duration and amount of purchase/service. The dependent variables are accumulated over a period of time and the independent variables are account details and/or customer profile data (including tenure).   For each of the dependent variable, a linear function of the independent variables, together with the other variables, is modeled, and estimated simultaneously (among the dependent variables).   The reduced model, which separates the dependent variables with the independent variables, is then used; from this, the profiles and characterization of revenue behavior is made. See Zellner (1962) and Zellner (1963) for details of seemingly unrelated regression models.

Tenure will account for uncertainty, while ARC will measure value. Combining tenure and ARC provides a stochastic valuation of CLV.

4   Illustration

We illustrate the methodology using transactional data derived over the most-recent 45-month period. It is ideal to include 3 to 4 years of data points to clearly understand consumer behavior. Very short data may only reflect random shocks in consumer behavior and will not characterize the true and long-term behavior of the customer. Over 2,000 customers were included in the sample, of which about 51% are active accounts. Majority were personal account-type (85%) and 12% other types (including corporate accounts). Ninety-four percent are regular customers, mostly females (55%), and at 30-40 years old (33%) or 40-50 years old (29%). The distribution by year of acquisition (year 0 as most recent at the time of study, year -1 is one-year back, year -2 is two-years back, and so on) is given in Table 1.

**Table 1. Distribution of Sample by Year of Acquisition**

Year	Frequency	Percentage
-11	42	1.32%
-10	90	2.83%
-9	89	2.79%
-8	135	4.24%
-7	92	2.89%
-6	272	8.54%
-5	337	10.58%
-4	394	12.37%
-3	446	14.00%
-2	728	22.86%
-1	404	12.68%
0	156	4.90%

The tenure data is composed of two types – the completed tenure (i.e., historic), and the truncated tenure (i.e., active). Note that for the second model on tenure analysis, non-censored data are those customers whose lifetime ended and whose acquisition dates fall within the observed period. Left-censored data happens when a historic customer's acquisition date is prior to (or to the left of) the observation period. Right-censored data happens when an active customer's acquisition date is within the observation period.   Interval censoring happens for active customers whose commencement date is prior to the observation period. Thus, completed tenure customers have either non- or left- censored data, while truncated tenure customers have either right- or interval-censored data.

4.1   Probability of survival

Survival probability function (i.e., the expected lifetime distribution) across all segments follows a Weibull distribution. Overall expected lifetime (EL) at the 50th percentile (EL50) is at 75 months, that is, for a given customer, there is a 50% chance of survival comes his 75th month of engagement with the company. The plot of the survival function is given in Figure 3.

Figure 3. Overall Survival Model (i.e., EL model)
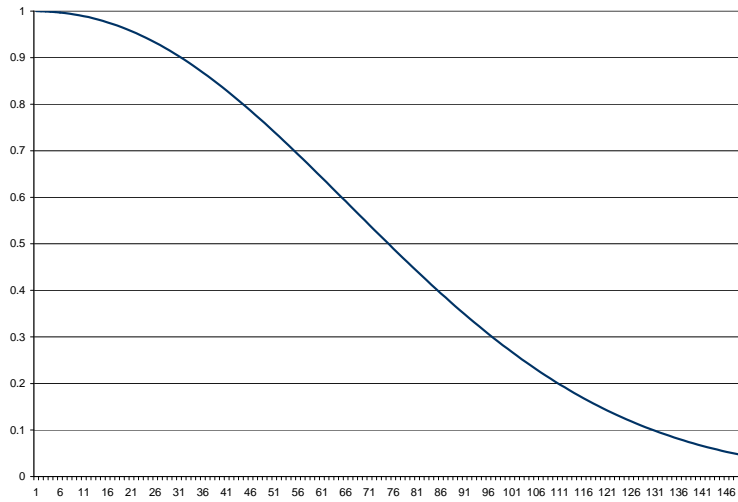
Across age groups, those aged less than 30 years old had the lowest probability of survival (i.e., staying with the company) with EL50 only at 5.5 years, while those aged over 50 years old had the highest probability of survival with EL50 at 6.5 years. Those within the 30-39 years old and the 40-50 years old were relatively at mid-level, with EL50 at 6 years. The plots of the survival functions are in Figure 4, and the associated probabilities by 12-months interval are given in Table 2.
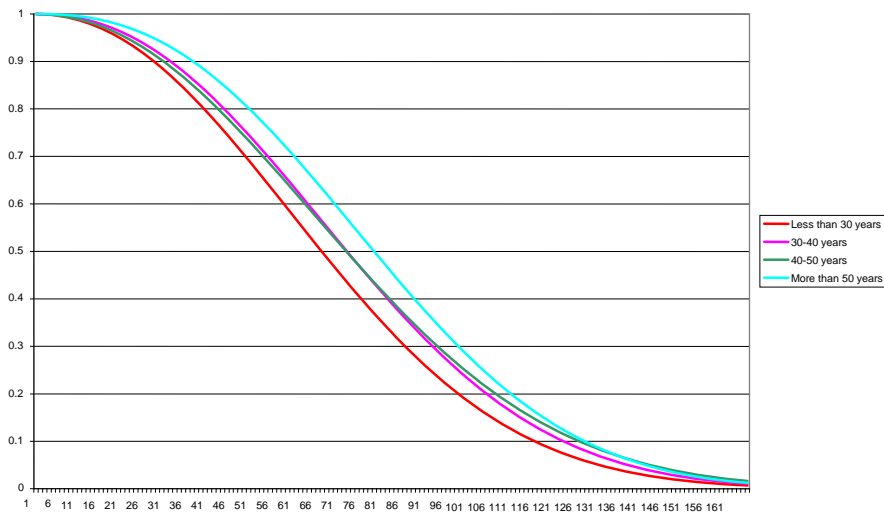
Figure 4. EL models across Age Groups

Table 2. Probability of Survival By Age Group

Tenure (in Months)	Probability of Survival			
	Age			
	Less than 30	30-40	40-50	Over 50
1	0.9999	1.0000	0.9999	1.0000
12	0.9838	0.9890	0.9861	0.9938
24	0.9284	0.9471	0.9389	0.9655
36	0.8355	0.8712	0.8591	0.9076
48	0.7142	0.7656	0.7533	0.8192
60	0.5783	0.6402	0.6316	0.7056
72	0.4427	0.5076	0.5055	0.5766
84	0.3196	0.3805	0.3856	0.4448
96	0.2174	0.2690	0.2801	0.3224
108	0.1390	0.1788	0.1934	0.2186
120	0.0835	0.1116	0.1269	0.1381
160	0.0096	0.0143	0.0213	0.0171
165	0.0069	0.0105	0.0163	0.0123

The model above can be used in customer relationship planning. Suppose there is a new customer who is less than 30 years old. Three scenarios are considered: (1) an engagement with assured earnings of PhP 800 per month for a period of 24 months and will not change the engagement afterwards; (2) an engagement with assured earnings of PhP 800 per month for a period of 24 months but will downgrade the engagement to PhP 500 afterwards; and (3) an engagement with assured earnings PhP 800 per month for a period of 24 months and will increase the engagement to PhP 1,200 afterwards. The expected lifetime values are computed from Table 2 and summed up to tenure with significant probability of survival. A less than 30-year-old customer will have an expected lifetime of 69.44 months and within the first 24 months, the expected lifetime is only 23.41 months since there is a non-zero chance that the customer would churn prior to the second anniversary of the engagement. Suppose that incentives amounting to PhP 15,000 will be offered. Considering that a contract for 24 months will be imposed and the expected value of tenure by 24 months is 23.41, the expected engagement should be at least PhP 640.75 per month to recover the investment of PhP 15,000. At this rate, the lifetime customer value is PhP 44,485. Considering the actual engagement of PhP 800 per month for 24 months, the expected worth of the customer is PhP 18,728. Note that this is about 25% earnings from the initial investment. Expected worth of the customer for some tenure duration are summarized in Table 3.

Table 3. Expected Worth of a Customer Less than 30 Years Old

Tenure	Case1		Case 2		Case3	
	Contract Engagement	Expected Value	Contract Engagement	Expected Value	Contract Engagement	Expected Value
1	800	799.94	800	799.94	800	799.94
12	800	787.00	800	787.00	800	787.00
24	800	742.74	800	742.74	800	742.74
25	800	737.63	500	461.02	1200	1106.44
26	800	732.30	500	457.69	1200	1098.45
27	800	726.77	500	454.23	1200	1090.15
28	800	721.03	500	450.65	1200	1081.55

| 29 | 800 | 715.10 | 500 | 446.94 | 1200 | 1072.65 |
30	800	708.97	500	443.11	1200	1063.45
160	800	7.66	500	4.79	1200	11.49
165	800	5.55	500	3.47	1200	8.32
Total Lifetime Value		**55,554.83**		**41,746.41**		**73,966.06**

Across account type, corporate accounts had the highest likelihood of survival within the first 10 years, with EL50 at 7 years. Retailers had the lowest likelihood during the first 7 years but had the highest likelihood after 10 years and with EL50 only at 5 years and 5 months. Personal accounts are at mid-level during the first 7 years and become lowest thereafter, with EL50 at 6 years and 1 month. The distribution functions are in Figure 5.

Figure 5. EL Models across Account Type
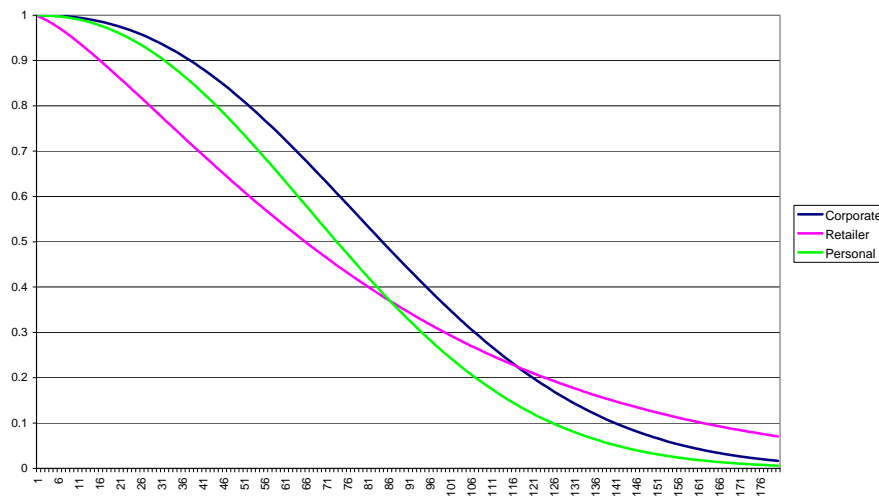
Across gender, the hazard functions are comparable but with that of males slightly higher. Females' EL50 is at 6 years while that of males is at 6.5 years. The plots are in Figure 6.

Figure 6. EL Models across Gender
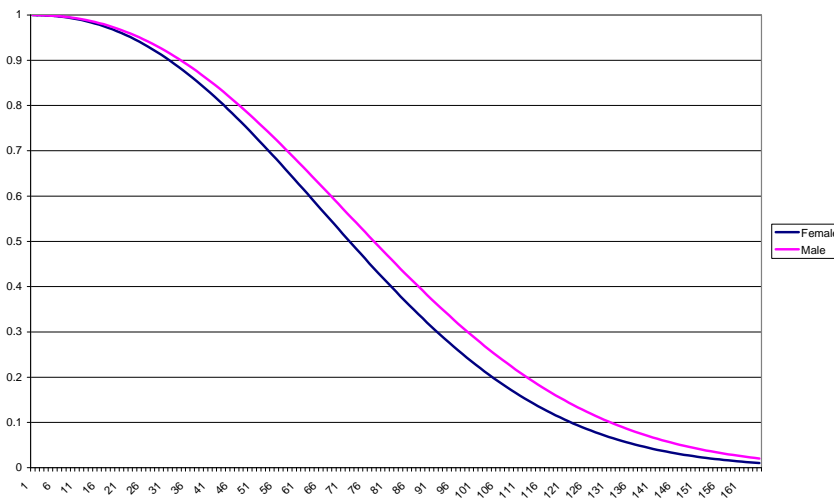
Differences in market segments are very much evident, with very high discrepancy between regular and premium customers (see Figure 7). EL50 for regular customers is nearly 6 years, while that of premium customers is more than 10 years.

Figure 7. EL Models across Market Segment
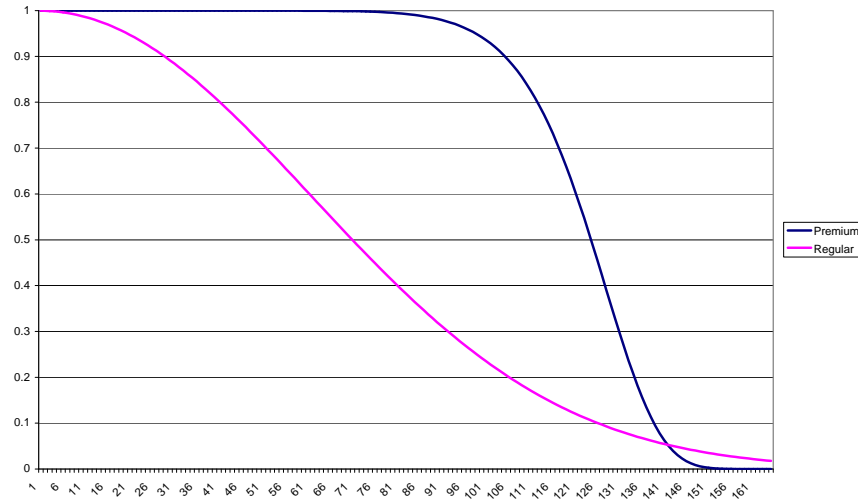
4.2   Tenure analysis

Different models were considered with the covariates present in the analyses. Payment modes were also considered in modeling – whether customers pay in full or partial, on-time or late, or at a specific mode (cash, cheque, etc.). Unsegmented (i.e., all data included) and segmented (i.e., for each pre-identified segments like account type, market segment) models were generated as a pre-process for identifying possible indicators for the final EOL model. The final EOL model had the following significant covariates – indicator if premium, indicator for account type, tenure (at the beginning of the accumulation period), indicator if account is over 2 years, and usage details (frequency, duration and amount of specific services). The EOLs (average additional tenure/remaining years with the company) of the sample data across different profiles are summarized in the following table (but note however that these were computed based on average values on the transaction details).

Table 4. Average EOL by Profile

	Profile	Average EOL (in Years)
Over-all	All data	2.85
	Corporate	2.22
	Retailers	1.46
Account Type	Personal	3.05
	Less than 30 years old	3.68
	30-40 years old	3.04
	40-50 years old	3.00
Age Group	Over 50 years old	2.83
	Female	3.13
Gender	Male	2.90

4.3   Revenue analysis

To model ARC, we considered customer's age, gender, account type, activity (historic or active) and tenure, together with the number of supplementary accounts as independent variables. Note that three different sets of dependent variables were considered (on frequency, on duration, and on amounts, across different services/products) via structural equations (with dependent variables as exogenous within a set), thus ARC can be predicted either through regularity of usage/purchase, extent of use, or outright cost. Effects of the independent variables vary across each of the dependent variables.

4.4   Integration of tenure and ARC models

In the absence of transactional data, the hazard function models can be used in scoring for CLV, with customers having high likelihood to stay to be given higher CLV score and better incentives. However, the CLV scoring becomes more dynamic and/or efficient when referenced to static data-- in this case, via the different transactional and profile data. Prioritization scheme can then be implemented on a timely basis. High-valued loyal customers are those expected to stay longer with the company and are expected to have high engagement (in terms of usage/purchase of services/products, and thus higher profitability). Devoted but "unexcited" customers are those expected to have high tenure but have low engagement, thus up-sell and/or cross-sell efforts may be employed. Urgent targets are those perceived to terminate soon but have high engagement, thus the company must come up with retention campaigns.

Single scoring, on the other hand, entails more specific company directives. With the current tenure and ARC models, the immediate next step is to identify appropriate "weights" aligned with the company objectives. If profitability is of top priority, then weights may be skewed towards customers with high predicted ARC. Otherwise, if retention is priority, then weights may be assigned heavily to those with high likelihood to stay with the company. If profitability and retention are of equal importance, then weights may be equally distributed.

5   Conclusions

There are differences in customer behavior among different segments of customers. Knowing the differences, and equivalently, identifying such characteristics of customer base are easily explained by or achieved with CLV modeling. There were generally two different prongs of customer behavior modeling proposed, both the tenure and the revenue analyses illustrate the importance of valuation of a customer to the company – by looking into transactional and/or profile data where the company is able to assess how customers "relate with" the business based on expected (and measurable) quantities.

For companies whose marketing strategy is centered on what the customer needs or expects, or whose business objective evolving around customer experience, CLV modeling remains a vital tool in meeting such directions. Though CLV models take on different approaches, different data mining techniques are proven useful in understanding deeper the behavior of the customers and at the same time assess the value of customers on a timely basis.

References

Bauer, H., Hammerschmidt, M., & Braehler, M. (2003). The customer lifetime value concept and its contribution to corporate valuation. *Yearbook of Marketing and Consumer Research*, *1*, 47-67.

Benoit, D., & Poel, D. (2009). Benefits of quantile regression for the analysis of customer lifetime value in a contractual setting: An application in financial services. *Expert Systems with Applications*, *36*, 10475-10484.

Berger, P., & Nasr, N. (1998). Customer lifetime value: Marketing models and applications. *Journal of Interactive Marketing*, *12*, 17-30.

Berger, P., Eechambadi, N., George, M., Lehmann. D., Rizley, R., & Venkatesan, R. (2006). From customer lifetime value to shareholder value: Theory, empirical evidence, and issues for future research. *Journal of Service Research*, *9*, 156-167.

Bose, I., & Chen, X. (2010). Exploring business opportunities from mobile services data of customers: An inter-cluster analysis approach. *Electronic Commerce Research and Applications*, *9*, 197-208.

Chan, S., & Ip, W. (2011). A dynamic decision support system to predict the value of customer for new product development. *Decision Support Systems*, *52*, 178-188.

Crowder, M., Hand, D., & Krzanowski, W. (2007). On optimal intervention for customer lifetime value. *European Journal of Operational Research*, *183*, 1550-1559.

Dwyer, F. (1989). Customer lifetime valuation to support marketing decision making. *Journal of Direct Marketing*, *3*, 8-15.

Glady, N., Baesens, B., & Croux, C. (2009a). Modeling customer lifetime value. *European Journal of Operational Research*, 197, 402-411.

Glady, N., Baesens, B., & Croux, C. (2009b). A modified Pareto/NBD approach for predicting customer lifetime value. *Expert Systems with Applications*, 36, 2062-2071.

Gupta, S., & Lehmann, D. (2003). Customers as assets. *Journal of Interactive Marketing*, *17*, 9-24.

Gupta, S., Hanssens, D., Hardie, B., Kahn, W., Kumar, V., Lin, N., Ravishanker, N., & Sriram, S. (2006). Modeling customer lifetime value. *Journal of Service Research*, *9*, 139-155.

Han, S., Lu, S., & Leung, S. (2012). Segmentation of telecom customers based on customer lifetime value by decision tree model. *Expert Systems with Application*, *39*, 3964-3973.

Khajvand, M., Zolfaghar, K., Ashoori, S., & Alizadeh, S. (2011). Estimating customer lifetime value based on RFM analysis of customer purchase behavior: Case study. *Procedia Computer Science*, *3*, 57-63.

Kim, G., Kim, A., & Sohn, S. (2009). Conjoint analysis for luxury brand outlet malls in Korea with consideration of customer lifetime value. *Journal of Service Research*, *9*, 139-155.

Lee, J., Lee, J., & Feick, L. (2006). Incorporating word-of-mouth effects in estimating customer lifetime value. *Database Marketing and Customer Strategy Management*, *14*, 29-39.

Ma, M., Li, Z., & Chen, J. (2008). Phase-type distribution of customer relationship with Markovian response and marketing expenditure decision on the customer lifetime value. *European Journal of Operational Research*, *187*, 313-326.

Malthouse, E., & Blattberg, R. (2005). Can we predict customer lifetime value? *Journal of Interactive Marketing*, *19*, 2-16.

Mikkonen, K. (2011). Exploring the creation of systemic value for the customer in advanced multi-play. *Telecommunications Policy*, *35*, 185-201.

Reinartz, W., & Kumar, V. (2003). The impact of customer relationship characteristics on profitable lifetime duration. *Journal of Marketing*, *67*, 77-99.

Rosset, S., Neumann, E., Eick, U., & Vatnik, N. (2003). Customer lifetime value models for decision support. *Data Mining and Knowledge Discovery*, *7*, 321-339.

Rust, R., Kumar, V., & Venkatesan, R. (2011). Will frog change into a prince? Predicting future customer profitability. *International Journal of Research in Marketing*, *28*, 281-294.

Ryals, L. & Knox, S. (2005). Measuring risk-adjusted customer lifetime value and its impact on relationship marketing strategies and shareholder value. *European Journal of Marketing*, *39*, 456-472.

Venkatesan, R., & Kumar, V. (2004). A customer lifetime value framework for customer selection and resource allocation strategy. *Journal of Marketing*, *68*, 106-125.

Wu, S., & Li, P. (2011). The relationship between CRM, RQ, and CLV based on different hotel preferences. *International Journal of Hospitality Management*, *30*, 262-271.

Zellner, A. (1962). An efficient method of estimating seemingly unrelated regressions and tests for aggregation bias. *Journal of the American Statistical Association*, *57*, 348-368.

Zellner, A. (1963). Estimators for seemingly unrelated regression equations: Some exact finite sample results. *Journal of the American Statistical Association*, *58*, 997-992.