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Measuring the Success of Retention Management Models Built on Churn Probability, Retention Probability, and Expected Yearly Revenues

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ABSTRACT

In this paper, we claim that optimal retention management models should consider not only churn probability but also retention probability and expected revenues from target customers. To validate our claim, we develop and compare five retention management models based on churn probability, retention probability, expected revenues, and combination of these models along with different evaluation metrics. Our experimental results show that the retention management model with the highest accuracy in predicting possible churners is not necessarily optimal because it does not consider the probability of accepting retention promotions. In contrast, the retention management model based on both churn and retention probability is the best in terms of predicting customers who are most likely to positively respond to retention promotions. Ultimately, the model based on expected yearly revenue of customers accrues the highest revenues across most target points, making it the best model out of five retention management models.

Keywords

Customer Relationship Management; Business Intelligence; Churn Management; Retention Management

INTRODUCTION

Customer churning has forced many companies in competitive markets to shift their strategic focus from customer acquisition to customer retention. For example, two related studies claimed that a significantly higher portion of marketing budget should be allocated for retention program than acquisition program to maximize the effects of marketing activities (Reinartz et al., 2005). Gupta et al. (2004) also concluded that a 1% improvement in retention can improve customer profitability by about between 5 and 50 times than a similar improvement in margin and acquisition cost. To identify target customers for retention campaigns, both marketing and data mining researchers have presented various customer selection models (Lee et al., 2011 and citations therein). In particular, with exceptionally high annual churn rates (20–40%), the firms in mobile telecommunications industry want to accurately identify which customers are most likely to terminate the current relationship by estimating the churn probability for each customer. We, however, claim that marketing managers should consider not only churn probability but also the probability of accepting retention offers (i.e., retention probability) or expected revenue to maximize the outputs of marketing campaigns.

In order to propose more effective retention management models, we consider three major requirements for successful retention management programs. The first requirement of retention management programs is to accurately identify customers who are most likely to churn or to accept a retention offer. Once the churn probability is estimated for each customer, a marketing manager sorts customers based on the estimated churn probability and chooses top $x\%$ of customers and offers them retention marketing promotions (Kim et al., 2005; Lee et al., 2011). The second requirement of retention management models is to focus on customers who are most likely to accept retention promotions from possible churners. Note that the probability of accepting retention marketing promotions may be dependent on factors like switching costs (Chen and Hitt, 2002) and customer satisfaction (Mozer et al., 2000). The third requirement implies that the service provider should allocate the limited marketing resources to customers who are most likely to generate higher profits. According to this requirement, customers who generate higher expected revenues are preferred to customers who generate lower expected revenues (Venkatesan and Kumar, 2004). Other studies also indicate that not all loyal customers are profitable and not all profitable customers loyal (Kumar and Shah, 2004), implying that it is necessary to manage loyalty and profitability simultaneously. Based on these observations, we consider both the probability of churning and the retention probability along with service fees associated with the service plans of customers to compute expected revenues from customers.

The ultimate goal of this paper is to propose an effective and practical retention marketing management framework that not only considers churn and retention probability but also life time value of target customers. For this purpose, we first develop four retention management models based on customer's churn probability, retention probability, and both churn and retention probability, and expected yearly revenue weighted by the estimated churn and retention probability. Then, we compare these models with a random marketing model on a real world data set using a well-known evaluation metric, hit rate (i.e., true churning identification ratio), and a newly developed metric, retention rate (i.e., identification ratio of customers who accept retention offers).

The remainder of this paper is organized as follows. In Section 2, we briefly review relevant literatures to identify factors that affect retention behaviors of customers. Section 3 describes the research framework, and introduces data sets and evaluation metrics used in our experiments. We present computational results and interpret managerial implications of outputs. Section 5 discusses the conclusions we reached based on these experiments and outlines directions for future research.

LITERATURE REVIEW

To consider the retention probability in retention management systems, we identify two main determinants of retention decision, satisfaction and switching costs (Gerpott et al., 2001; Gustafsson et al., 2005).

Customer Satisfaction

Customer satisfaction has been known to be one of the most important positive determinants of customer retention. Several studies (Rust and Zahorik, 1993; Bolton, 1998) found that there exists a positive relationship between overall customer satisfaction and customer retention, and profitability. It is known that customer satisfaction is a subjective assessment of services quality, depending on "will expectations" (i.e., the quality to be expected), "should expectations" (i.e., the quality that should be met), and "actual" service quality over periods (Boulding et al., 1993). For example, when actual service quality is below an expected service level from the customer's perspective, the customer perceives decreased satisfaction. Other studies reported that well-managed complaint management systems can significantly boost customer satisfaction and customer retention (Fornell and Wernerfelt, 1987; Solnick & Hemenway, 1992; Keaveney, 1995). In addition, the positive relationship between satisfaction and profitability has been confirmed (Rust et al., 1995; Hegji et al., 2007). For example, Anderson, Fornell and Mazvancherly (2004) and Ittner and Larcker (1998) show that 1% change in customer satisfaction index can lead to a \$240-275 million improvement in firm value. However, it is known that a drop in satisfaction produced twice the impact on return on investment (ROI) than an increase in satisfaction (Anderson and Mittal, 2000) and the impact strength varies across industries as well as across firms within an industry (Anderson et al., 1997; Anderson et al., 2004).

According to several studies (Bolton, 1998; Gerpott et al., 2001), the satisfaction level of mobile phone service users has been known to be affected by three main factors: call quality, price, and customer support. For example, according to a study (Gale, 1992), while over 90% of customers who rated the company's service quality as excellent expressed their willingness to repurchase from AT&T, customers rating the service as good, fair, or poor expressed much low repurchase willingness (60%, 17% and 0%, respectively). This also suggested that a certain change in experienced service quality (e.g., when the service-quality change from fair to good) most greatly impact the repurchase decision than any other changes in service quality ratings. Note, however, that due to the subjective nature of satisfaction assessment, these factors are not perceived as equally important by all the customers. For example, it was found that call quality plays an important role to determine the retention tendency of both Germans and Koreans while price and customer support do so only for either Germans or Koreans (Gerpott et al., 2001; Kim et al., 2004).

Switching Costs

One of major roles of marketing managers is to boost the customer loyalty toward brand and service of the service provider so that customers behaviorally purchase goods and services repeatedly, resulting in steady increase of frequency or relative volume of purchasing (Tellis, 1988). In addition, it is also known that loyal customers are attitudinally different from other customers in terms of repurchase intentions, intention to recommend to others, likelihood of switching, and likelihood of buying more (Mittal and Kamakura, 2001). In particular, loyal customers are believed to maintain a relationship with the focal firm, engage in positive word of mouth, and repeat purchasing. However, it is very possible that even satisfied and loyal customers may leave the current service provider if they find attractive goods and services at more affordable terms from other service providers. While, it is easy to imagine that dissatisfied and non-loyal customers are more likely to terminate relationships with the current service provider, even dissatisfied mobile telecommunication service customers may maintain their current contractual relationships with the service provider because of high switching costs (Bendapudi and Berry, 1997).

Several studies (Gerpott et al., 2001; Kim et al., 2004) identify loyalty points and membership card programs as major examples of switching costs. According to these studies, the customers' expectation that all the membership benefits and

accumulated points be lost right after they terminate the current relationship prevents them switching to other service providers. We also note that customers do not wish to terminate their contractual relationships even when they do not lose any loyalty points or other benefits with current service providers. For example, customers with many active subscribers in the same family, with many mobile handsets, or with sophisticated handsets or service options are more likely to accept retention promotions because of their high switching costs. Note that these customers should pay higher social or opportunity costs such as searching for new service providers with affordable service charges, purchasing new handsets for many subscribers (handsets are specialized to each service provider), transferring their new phone numbers to their friends, and so on. Therefore, these customers can significantly reduce their switching costs by sticking to the same service provider as long as appropriate retention offers are made. Note also that these customers may generate large portions of revenues because of their family service plans, and sophisticated handsets and service options.

RETENTION MANAGEMENT MODELS

Data Sets and Preprocessing

Our research framework consists of three sequential steps based on typical customer relationship management (CRM) processes, data preparation, model construction, and model evaluation as illustrated in Figure 1. The first step is mainly for data preparation and includes multiple steps such as preprocessing of missing values, removing uninformative categorical variables, and calculating churn and retention probability. Then, in the second step, five retention management models including a random model are calibrated using churn and retention probability, and expected yearly revenue. Finally, in the third step, five models are compared and evaluated along five evaluation metrics such as hit rates, retention rates and expected yearly revenue. All these steps will be explained in detail in the current and subsequent sections.

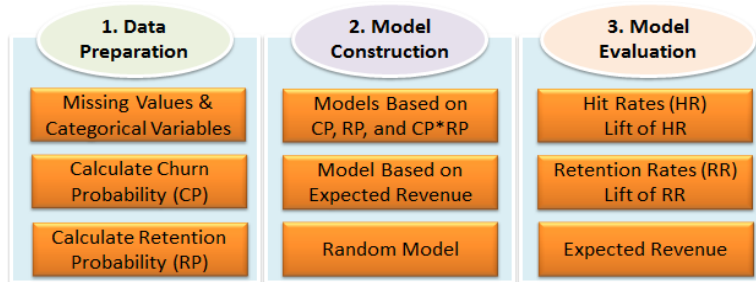


Figure 1. Research framework

As the first step of data preparation, we preprocess the data sets from the Teradata Center for CRM at Duke University by eliminating several variables with little predictive information and many missing values as illustrated in (Kim, 2006). The processed version of data sets consists of the training set containing 67,181 observations with 32,862 churners and the test set containing 34,986 observations with 619 churners. Both data sets contain 123 predictors including 11 categorical variables and 112 continuous variables. Due to the limited availability of records with customer's response to retention offers, we decided to artificially generate customers' responses to retention promotions based on multiple variables that reflected customer satisfaction and switching costs. We set the ratio of positive respondents to retention promotion to about 20% (7,127/34,987) of all the customers in the test sets.

Calculating Churn and Retention Probability

After we preprocess data sets, we estimate churn and retention probability for each customer in the database to select target groups for retention management programs. To estimate churn probability, PLS is employed for churn prediction classifier because of its minimum requirements on measurement scales and residual distributions, multicollinearity among variables, and comprehensibility through variable important in projection (VIP) scores (Lee et al., 2011). Once churn probability for each customer is estimated, the next step is to estimate the retention probability using variables related to switching costs and customer satisfaction scores with the current service provider. After careful reviews of the data sets and literature review, we identify several variables relevant to switching costs. These variables include two user related variables (# of active subscribers, 7 categories; # of unique subscribers, 11 categories), two phone related variables (# of phones, 14 categories; # of phones models, 14 categories), and phone price (7 categories). Note that we discretize each of these variables into multiple categories by considering value distributions to rank each customer and hence estimate retention probability based on ranking from each variable. We summarize our approach to estimate a retention probability (RP) based on each variable's ranking as follows:

- Sort all the customer records in the descending order of the values of a variable related to switching costs (e.g., # of active subscribers that reflects the complexity of service plan).
- Rank each record using numbers between 1 and R , where R represents the number of categories. For example, if there are total 7 different values for a chosen variable, there will 7 ranks (from 1 to 7). Customer records with a higher rank (i.e., rank 1) are more likely to accept retention promotions.
- Compute and assign the reciprocal rank (RR) as a retention probability for each record. The RR for record i (RR^i) whose rank is r can be computed as $1/r$.
- Compute an aggregated retention probability from retention probabilities based on each switching cost variable as follows: the following formula: $RP^{\text{switch}} = \text{average}(\text{average of RPs based on two user related variables, average of RPs based on two phone related variables, RP based on phone price variable})$.
- Linearly transform its value between 0 and 1 and denote it as NRP^{switch} .

To compute the retention probability based on customer satisfaction, we first identify variables that may indicate customer satisfaction from the data sets. To this end, we decide to use two variables that can be combined to measure customer satisfaction based on call quality (or connectivity). In practice, we compute for each customer a service failure rate (SFR) by taking the ratio of the mean value of dropped or blocked data and voice calls to the total number of attempted data and voice calls. Then the retention probability based on satisfaction, $RP^{\text{satisfaction}}$, is computed as follows: $RP^{\text{satisfaction}} = 1 - \text{SFR}$. Finally, it is linearly transformed into $NRP^{\text{satisfaction}}$ so that its value is between 0 and 1. Then, the final retention probability based on switching costs and satisfaction, RP^{Final} (in short, RP), is computed as follows: $RP = NRP^{\text{switch}} \times NRP^{\text{satisfaction}}$. Note that we tested several ways of combining NRP^{switch} and $NRP^{\text{satisfaction}}$ (e.g., taking an average of them or multiplying them with equal weights) to compute the final retention probability. However, the experimental results are similar and hence we present only outputs based on $RP = NRP^{\text{switch}} \times NRP^{\text{satisfaction}}$.

Retention Management Models

To highlight the importance and usefulness of churn probability, retention probability, and expected revenues in retention management models, five models are calibrated. The first three models are based on churn probability (Model^{CP}), retention probability (Model^{RP}), and both churn and retention probability (Model^{CRP}) respectively to select target customers for retention promotions. Two other models include one model that selects target customers based on expected yearly revenue from customers (Model^{YR}), and the other that selects target customers randomly (Model^{RM}). The first model, Model^{CP}, is purely based on the estimated churn probability and reasoning behind this model is that marketing managers should focus on customers who are most likely to churn. While this model may perform best in terms of predicting who are most likely to terminate the relationship, it may not be accurate in predicting who are most likely to accept retention offers when an appropriate offer is made, and hence may not be the best model to maximize the revenue of retention campaigns. The second model, Model^{RP}, selects target customers in the descending order of the estimated retention probability. The reasoning behind this model is that customers with the highest estimated churn probability are not necessarily the best candidates for retention management programs because they are still most likely to terminate the relationship by refusing retention offers.

The third model, Model^{CRP}, selects target customers based on both churn and retention probability by multiplying two estimated probabilities (or taking an average of two probabilities). Then, ideal target customers are those who are most likely to churn if no retention program is offered but who want to maintain the service relationship when an appropriate intervention program is initiated from the service provider. While allocating limited retention management resources to customers who are most likely to accept the retention promotions (e.g., ones with high switching costs) among customers with high churn probability (e.g., ones whose contractual period is about to end soon) is perfectly reasonable, the profitability of the target customers is not considered in this model. The fourth model, Model^{YR}, considers expected yearly revenue on top of the estimated churn and retention probability in Model^{CRP}. The reasoning behind this model is that even customers who are most likely to accept the retention offers and keep the current service relationship may not be most profitable customers to the service provider because they may generate low high expected yearly revenue. The last model, Model^{RM}, selects target customers randomly and is included as a baseline model to measure the effectiveness of other marketing models.

EXPERIMENTAL RESULTS

Evaluation Metrics

In this study, retention management models are evaluated in terms of predictive accuracy (e.g., hit rate and retention rate), improvement compared with random model (e.g., lift of hit rates and retention rates), and marketing effectiveness (e.g., expected yearly revenue). First of all, hit rate and lift curve of hit rates are adopted to numerically quantify the predictive power of models and graphically represent the performance for easy comparison, respectively. The hit rate is defined as the number of correctly identified churners out of churning candidates in this study. For example, if the model is required to select

1000 customers who are most likely to churn from 10,000 observations, and 100 of them turn out to be one of 500 actual churners, then a hit rate at target point 10% ($1000/10,000=10\%$) is 20% ($100/500=20\%$). Note that a target point is a proportion of chosen records for marketing campaign.

While hit rate and lift curve of hit rates can quantify the predictive power of models, they are not ideal to measure the effectiveness of a retention management program that can be measured by quantifying how many identified churners accept the retention offer and maintain their relationship with the service provider. For this purpose, The retention rate is defined as the number of churners who accept the retention offer out of identified churners. The lift curve of retention rates shows the lift trend of retention rates across a range of target points, where a lift of retention rate is a ratio of the retention rate of a predictive model divided by the retention rate of a random model. Finally, the expected yearly revenue generated by target customers is also used to compare models.

Hit Rates and Lift of Hit Rates

We first compare all the five retention management models in terms of accurately predicting churners using two metrics: hit ratio and lift of hit rates. Note that Model^{CP} is expected to perform best in these evaluation metrics because it is specifically designed to predict churners based on known examples of churners in training data sets. Figure 1 confirms our conjecture. Among all the models, Model^{CP} perform best followed by Model^{CRP}, Model^{RP}, Model^{YR}, and Model^{RM}. Model^{CRP} was the second best mainly because it uses both churn and retention probabilities to finalize retention management targets while Model^{RP} only considers retention probability, making it inferior to Model^{CP} and Model^{CRP}. However, Model^{RP} performs better than Model^{YR} and Model^{RM} that do not consider either estimated churn or retention probability at all to identify customers for retention management campaigns. Note that the collection of hit rates of Model^{RM} across target points follows the diagonal line, resulting in $x\%$ of correctly identified hit records at $x\%$ target point by definition.

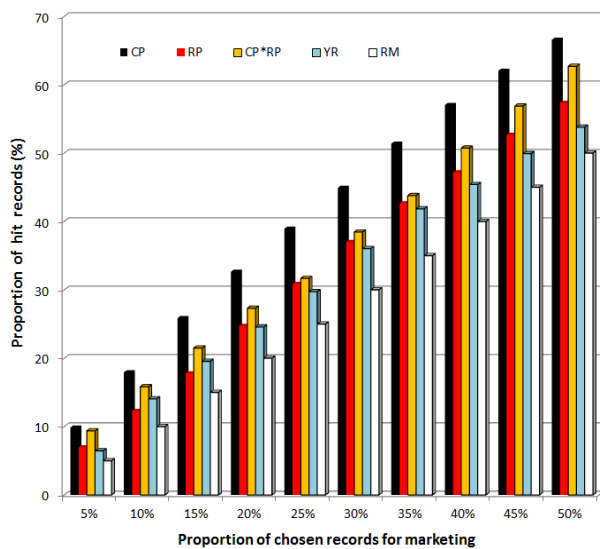


Figure 1. Hit rates of retention management models

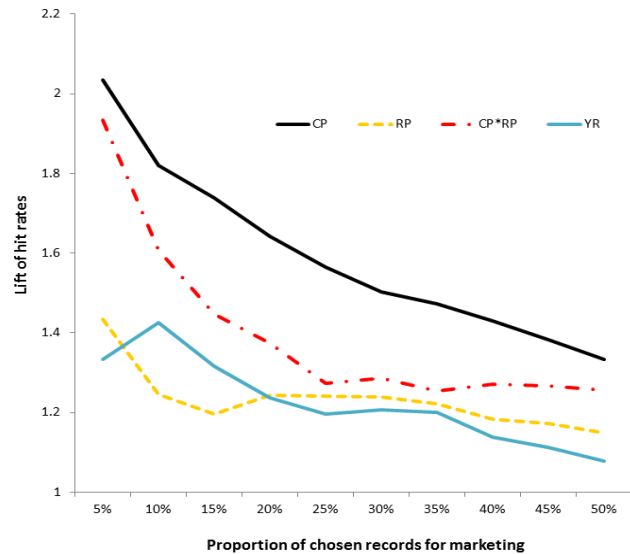


Figure 2. Lift curve of hit rates

Similar observations are made in Figure 2, which presents the lift of four retention management models compared with Model^{RM} over target points up to 50% of entire customer databases. All the models relatively perform much better than Model^{RM} at small target points (i.e., a small proportion of customer records is chosen for retention marketing campaign). For example, at target point 5%, Model^{CP} is 2.03 times better than Model^{RM}, while Model^{CRP}, Model^{RP}, Model^{YR} are 1.93, 1.43, and 1.33 times better than Model^{RM}, respectively. However, these prediction models lose their relative predictive power gains as more customers with lower churn probabilities are included in target customers at larger target points (i.e., larger proportions of customers are targeted for marketing campaigns). For example, when top 50% of entire customers are considered for retention management campaigns, Model^{CP} is only 1.33 times better than Model^{RM} in terms of predictive power gains compared with a random model.

Retention Rates and Lift of Retention Rates

In this section, we present retention rates and lift curves of retention rates of five retention management models in Figures 3 and 4, respectively. In terms of retention rates (=the proportion of correctly identified churners who positively responded to the retention promotions), Model^{CRP} performs best over most target points while Model^{CP} and Model^{RP} perform best or

second best over a certain range of target points. For example, Model^{CP} relatively performs well compared with Model^{RP} at smaller target points (e.g., 10% and 15%) or larger target points (e.g., 45% and 50%) while Model^{RP} performs better than Model^{CP} at target points between 20% and 35%. Since retention promotions are mainly suggested to customers who are most likely to churn (i.e., high churn probability) without promotions but who are mostly likely to accept retention offers (i.e., high retention probability), it is not surprising Model^{CRP} performs best in terms of retention rates. The comparable performance of Model^{CP} and Model^{RP} indicates that these two models are indirectly correlated mainly because customers who are most likely to accept the retention promotions are less likely to churn, indicating a negative relationship between them. The relative performance of retention management models compared with Model^{RM} in terms of lifts of retention rates becomes more significant. For example, at target point of 5%, Model^{CRP} is 6.5 times better than Model^{RM} in identifying retention records. In fact all the three models based on either churn or retention probabilities perform at least 5.0 times better than Model^{RM}. Overall, two models, Model^{RP} and Model^{CRP}, based on retention probability perform better than Model^{CP} across most target points in terms of retention rates and lift of retention rates.

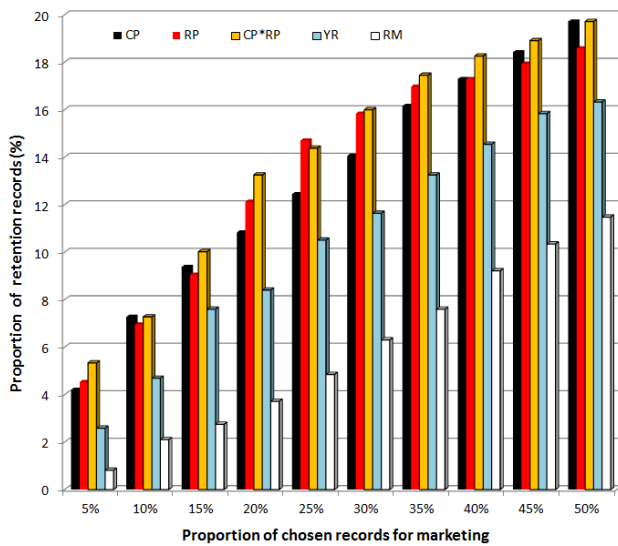


Figure 3. Retention ratio

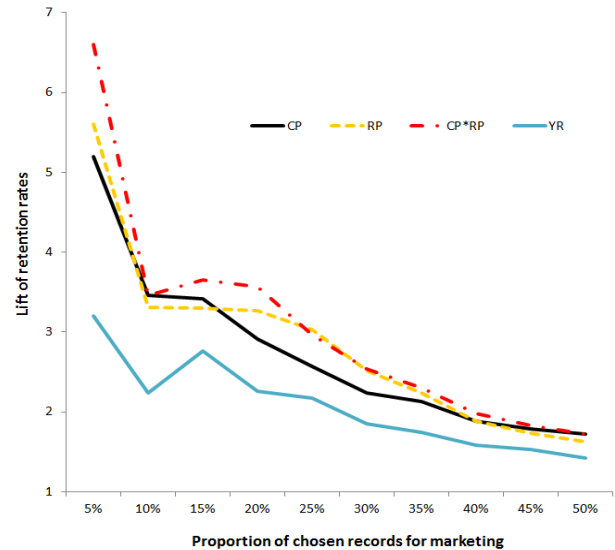


Figure 4. Lift curve of retention rates

Expected Yearly Revenue

Note that while Model^{YR} performs worst in terms of hit and retention rates as shown in previous sections, it does not mean that it is the worst retention management model. On the contrary, we claim that the performance of other models is optimistically overestimated and Model^{YR} performs best out of all retention management models when expected revenues from customers over service contract periods are used as an evaluation metric. Figure 5 presents the expected yearly revenue of five retention management models. We first note that while all the retention models perform significantly better than Model^{RM}, Model^{YR} generates the highest expected yearly revenue across all target points except 35% and 40%. In particular, it performs very well at smaller target points (up to 15%), which makes it even more attractive when only limited financial and human resources can be adopted for retention management programs. To our surprise, Model^{CP} also performs very well at smaller target points (up to 15%), insinuating accurate churn prediction itself is an important factor to maximize the expected yearly revenue of customers from retention campaigns. One interesting observation we made was that both Model^{RP} and Model^{CRP} perform better than Model^{CP} at larger target points where retention prediction becomes more important than churn prediction as more less promising customers are included in target customer groups. When less likely churners are targeted for retention management, only customers in target groups who accept retention offers will generate expected yearly revenue and hence their role become more important. Another important and interesting observation is that Model^{CRP} always performs better than Model^{RP}, indicating the importance of combining churn and retention probability simultaneously.

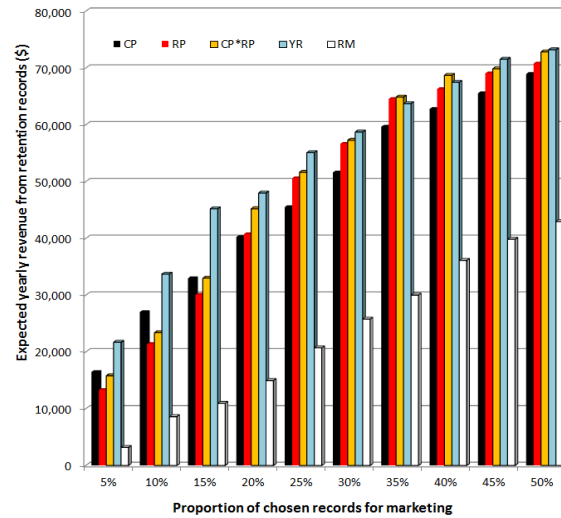


Figure 5. Expected yearly revenues

CONCLUSION AND FUTURE RESEARCH

In this paper, we propose five retention management models that consider churn probability, retention probability, and expected revenues with new metrics to measure the performance of models. Our experimental results show that Model^{CP} is the most accurate in predicting churners, while Model^{CRP} performs best in terms of predicting customers who positively responded to the retention promotions. We also notice that while Model^{YR} performs worst in terms of predicting churners and customers who accept retention offers, it generates the highest expected yearly revenue across most target points, making it the best model out of five retention management models. This is mainly because the ultimate goal of developing retention management models is not to have accurate marketing models in terms of accurately predicting churners but to maximize the revenue from retention marketing campaigns.

A promising direction of future research is to investigate the relationships among various retention models and validate their unique usefulness. The implication of this line of research is that marketing managers should consider their unique business needs and adopt and implement an appropriate retention campaign model. For example, when the service provider wants to maintain its current market share to put market entry barriers to prevent competitors from entering a saturated market, it may need a retention model like Model^{CP} and Model^{RP} so that it can accurately predict likely churners and contact them to understand the underlying attitudinal and behavioral reasons of churning behaviors. While the current research can be regarded as the first step toward this direction of research, it requires follow-up studies with other real-world data sets that include customer's actual or attitudinal responses to retention offers to quantitatively and qualitatively validate the findings.

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