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Author(s)	Hiramatsu, Ayako; Shono, Yuji; Oiso, Hiroaki; Komoda, Norihisa
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Subscriber Number Forecasting Tool Based on Subscriber Attribute Distribution for Evaluating Improvement Strategies

Ayako Hiramatsu[1], Yuji Shono[2], Hiroaki Oiso[3], Norihisa Komoda[2]
[1]Department of Information Systems Engineering, Osaka Sangyo University,
3-1-1, Nakagaito, Daitou, Osaka, 574-8530, Japan
ayako@ise.osaka-sandai.ac.jp
[2]Graduate School of Information Science and Technology, Osaka University,
2-1, Yamada-oka, Suita, Osaka, 565-0871, Japan
[3]Codetoys K.K., 2-6-8 Nishitenma, Kita-ku, Osaka, 530-0047, Japan

ABSTRACT

In this paper, a subscriber number forecasting tool that evaluates quiz game mobile content improvement strategies is developed. Unsubscription rates depend on such subscriber attributes such as consecutive months, stages, rankings, and so on. In addition, content providers can anticipate change in unsubscription rates for each content improvement strategy. However, subscriber attributes change dynamically. Therefore, a method that deals with dynamic subscriber attribute changes is proposed. According to the features of content improvement strategies, content providers decide the conditions and the rates of unsubscription changes. Then the unsubscription rate for each segment is recalculated. In the period doing which a content improvement strategy has not been launched, prediction accuracy in the following there months of the proposed (subscriber-based) prediction method was compared with the segment-based prediction method.

Keywords: simulation, modeling, customer retention

1. INTRODUCTION

In Japan the mobile content market has been expanding rapidly for two significant reasons. First, the combination of fixed monthly content fee and variable packet charges is reasonable for consumers. Second, the commissions charged by carriers who collect content fees are a very low 10%, which encourages the participation of content providers. However, consumers actually have to pay a large packet charge and their share of the monthly content fees of total payment is extremely low. Besides, carriers only collect monthly content fees to be allocated to the content providers. Content providers must therefore carry out effective marketing to attract more subscribers and prolong individual subscription periods.

Our target is game content provided through mobile phones. Subscriber behavior or intention has been analyzed [1][2][3] and strategies examined for prolonging subscription periods. However, because the actualization of new strategies is expensive, providers must select the most effective one. This paper, therefore, analyzes subscriber behavior and forecasts their numbers, based on the anticipated impact of new strategies to improve content. Based on subscriber game logs, this paper proposes a subscriber behavior model that expresses their subscription and unsubscription rates, and simulates their numbers [4][5][6][7].

Improvement strategies cause different effects for target subscribers. In our simulation method, since the behavior of subscribers who cancel differs by such attributes such as subscription periods, number of times the game is played, and so on, subscribers are divided into segments based on attributes. The unsubscribing rates of each segment can be estimated from past data. However, since subscribers who rank within 33% of the top score will be promoted the next stage the following month, subscriber attributes change dynamically. For this problem, a forecasting method to deal with dynamic changes of subscriber attributes is necessary. Subscribers are divided into segments by attributes. To cope with fluid subscriber attributes, an unsubscribing probability of each subscriber is estimated from the unsubscription rate of each segment. Using this unsubscribing probability, the simulation method predicts whether subscribers will unsubscribe in the next month. Because cancellation rates differ by targets of introduced strategies, the proposed simulation method prepares to input the effects of strategies for each subscriber attribute.

2. BACKGROUND OF SIMULATION

2.1 Target content

The target content is a quiz game provided by three mobile carriers. According to each carrier, there are no significant differences in game rules, although there are minor differences in display layout etc.

A game consists of a maximum of 15 multiple choice questions. If the 1st question is answered correctly, the player receives 10,000 points, and the points double for every correct answer. Apparently a lot of players can score a maximum number of points because it is easy to cheat through mobile phones. We count not only the points but also the time required to answer the questions for the final score, which is calculated at the end of each month. The best score in a game each month is the subscriber's score, which are the criteria for rankings. In this content, four levels of rankings, 1st through 4th stage (lowest to highest stage) are prepared and announced at the end of each month; only the top 33% players at each stage are promoted to the next stage. If subscribers cancel, all information up to the moment is lost. If a consumer rejoins, he starts from the 1st stage.

The cost is 180 yen (JPY) per month. The packet charge is about four JPY per quiz (= one page). For example, if the average number of quizzes in a game is eight, ten pages in total will be forwarded every game, which include two pages before and after the game. Therefore, the packet charge amounts to about 40 JPY. If a player plays the game 150 times a month, it will cost 6,000 JPY per month (6,180 including content fees). In the case of application versions, the packet charge is 20 JPY per download of a quiz pack of 90 questions and 200 to 400 JPY to download the application.

To prolong more subscriptions, prizes are provided to the leading scorers. In this content, only the five leading scorers at the highest stage receive prizes.

2.2Examples of improvement strategies

To explain improvement strategies, here are some examples that content providers have introduced:

- Introduction of a JAVA version
  At the beginning, this mobile game only provided a WEB version that required a large packet charge for subscribers, which dissatisfied many subscribers. So, the provider developed and introduced a JAVA version to reduce dissatisfaction.

- Relaxation of necessary condition for promotion.
  Subscribers used to be required to rank within the top 25% for promotion. Such a condition was too hard, and many subscribers complained. Accordingly, the provider changed the promotion conditions to 33%.

- Change in restrictions of number of times played.
  At the beginning, with WEB version game, subscribers could not play the game above 5 times a day. Many subscribers complained to the provider that they want to play more. Therefore, the restriction was changed as 150 times a month.

- Incentives
  In the present incentive system, only subscribers in the highest stage have a chance to get prizes. But, the provider introduced an incentive strategy that randomly awarded prizes to ten subscriber sin the lowest stages.

2.3 Change in number of subscribers

Monthly sales are in proportion to the number of monthly subscribers. If there are *x* subscribers on March 1, and in March *y* subscribers sign up and *z* subscribers cancel, then the number of subscribers on April 1 is $x+y-z$. These calculations are repeated *N* times when the number of subscribers after *N* months is forecasted. If both the numbers of new subscribers and unsubscribers are forecasted correctly, we can exactly forecast the number of subscribers.

3. METHOD FOR FORECASTING THE NUMBER OF SUBSCRIBERS

3.1 Outline of forecasting

For any six month period, new subscribers are about 1000, a figure that rarely changes. Therefore, the number of new subscribers is considered to be a roughly fixed number. On the other hand, unsubscribing rates depend on four attributes: subscription periods, stages, number of times played, and rankings.

As shown in Figure 1, based on four subscriber attributes registered in the log data, subscribers are divided into segments. The unsubscribing rate for each segment is determined statistically. Corresponding to new strategy targets, the provider inputs the subscriber attribute conditions and the changes in unsubscribing rates for each segment. Based on these rate changes, the simulation tool updates unsubscribing rates. For example, new strategy A offers subscribers above the 3rd stage many chances to get prizes. The change in unsubscribing rate in segments above the 3rd stage is set at -50% and rates below the 2nd stage are set at -20% by the provider. If the unsubscribing rate of segment one which includes subscribers of the 1st stage, is 50%, the updated cancellation rate is computed as 50% * (1 - 0.2) = 40%. Using such updated rates, the forecasting part simulates new subscribing, unsubscribing, and renewing subscriber attributes and calculates subscriber attribute data for the next month. Based on the subscriber attribute data of N month, the attribute data of N+1 month is simulated in the same way.

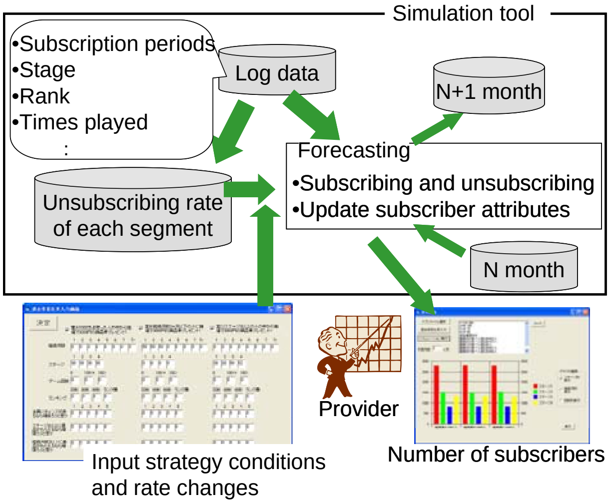

Figure 1. Outline of simulation tool

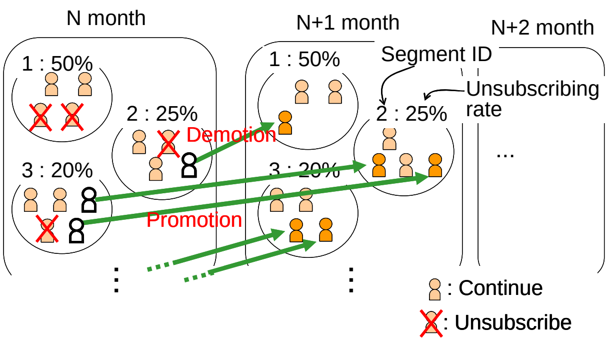

Figure 2. Segment changes of subscribers

However, as shown in Figure 2, segment changes of subscribers occur because of dynamic changes of subscriber attributes. For example, if the ranking of subscribers is within 33%, they will be promoted the next month. The rank of subscribers is also changed by the distribution of the number of correct answers and answer times. Therefore, since it is impossible to individually forecast subscriber numbers for every segment, it is necessary to update subscriber attributes every month and divide them into new segments.

To cope with such repetition, it is necessary to forecast each subscriber and specify who will cancel next month. Therefore, the cancellation rate of the segment is assigned to the unsubscribing probability of each subscriber in the segment. Using assigned probability, unsubscription for each subscriber is forecasted stochastically.

3.2 Unsubscribing rate of each segment

For simulating unsubscribing behavior, such probability for each subscriber is necessary. To determine cancellation probability, all subscribers are classified into groups by such features as stages, and number of times played to compute the unsubscribing rate of each group. For subscriber classification, using actual log data, we examined the relationship between unsubscribing rate and subscriber attributes, such as subscription period, stage, times played, and rank. We discovered values that change the unsubscribing rate and established them as thresholds for classification. The following are the thresholds of each attribute:

- Subscription period: four classes
  (one month, two months, three months, and more than four months)
- Stage : four classes (1st, 2nd, 3rd, 4th)
- Number of times played : three classes
  (0, 1-100, 101-)
- Ranking: four classes
  (no ranking, 0%-33%, 33%-66%, 66%-100%)

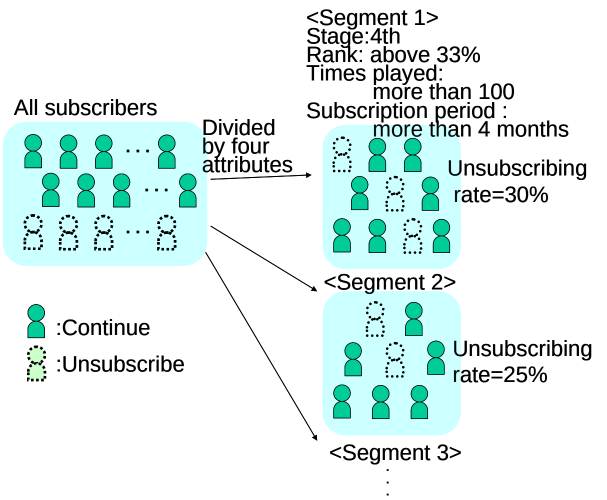

Figure 3. Calculation of unsubscribing rate

As shown in Figure 3, combinations of the above classes comprise 192 segments (=4*4*3*3) and the unsubscribing rate of each segment is calculated, which is assigned to the cancellation probability of each subscriber who belongs to the segment.

3.3 Changing unsubscribing rates for each strategy

According to the new strategy that targets specified subscribers, the changes in unsubscribing rates are different. For example, if the provider introduces a new strategy aimed at subscribers whose subscription periods are for three months, the behavior of subscribers who sing up for less than three months is changed. As shown in Figure 1, the providers establish conditions and changing unsubscribing rates. The simulation tool updates unsubscribing rates based on these input parameters. The following is an example. If the changing condition of the unsubscribing rate is in the 3rd stage, then the changing rate is -50%. If the condition is lower than the 2nd stage, then the changing rate is -20%. Figure 4 shows that changes in the conditions of the unsubscribing rates apply to each segment. An updated unsubscribing rate for each segment is calculated by the following formula.

Updated unsubscribing rate

= unsubscribing rate * (1 + changing rate/100)

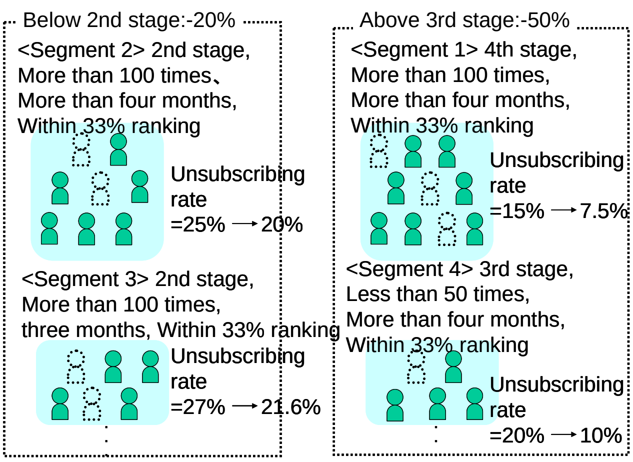

Figure 4. Applying changes in unsubscribing rates

3.4 Forecasting engine

The forecasting engine has two functions: operation of new subscribers or unsubscribers and updating subscriber attributes. By repeatedly using these two functions, it is possible to forecast the number of subscribers and their behavior over several months.

- Operation of new subscribers or unsubscribers
  There is little difference in the number of new subscribers each month as shown by the actual log data of the last six months. Therefore, it is assumed that the new subscriber number each month is regular. As shown in Figure 5, new subscribers in N+1 month are applied to attribute of new subscriber in N month. On the other hand, the forecasting engine decides whether each subscriber cancels stochastically by using a random number according to the unsubscribing probability assigned to each subscriber based on the unsubscribing rate of each segment.

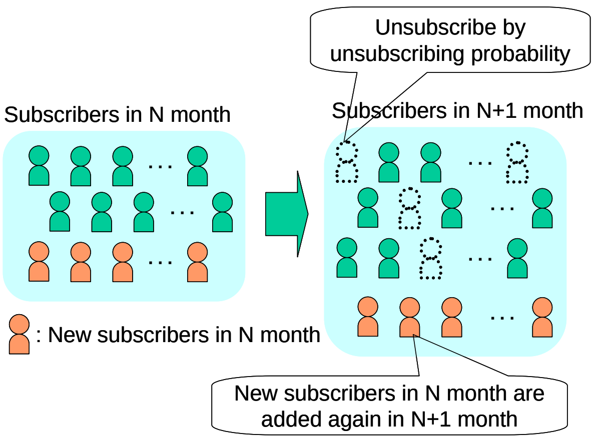

Figure 5. New subscribers and unsubscribers

- Updating subscriber attributes
  Using formulas in Figure 6, four subscriber attributes in N+1 month are calculated from data in N month. Based on the four attributes, subscribers are divided into segments and reassigned unsubscribing probability by segment.

	N month		N+1 month
Stage	S		S’
Rank	R	⇨	R’
Times played	N	Calculate	N’
Subscription period	M		M’

S’=if(R<33%) S+1; else S;
R’=R (Decide by distributions of
the number of correct answers
and answer times);
N’=N;
M’=M+1;

Figure 6. Updating subscriber attributes

4. EXPERIMENTS WITH ACTUAL DATA

4.1 Outline of experiment

For the following two purposes, we examined the proposed method with actual data.

- Evaluation of the forecasting method
  To evaluate the proposed forecasting method that decides the unsubscribing behavior of each subscriber, we compare results by the proposed method with the results by a forecasting method that decided the unsubscribing behavior of each segment. For this examination actual data for the period when no new strategy was introduced is applied.

- Evaluation for practical use

  A) Comparison of improvement strategies
  In practical environments, with the proposed tool the provider inputs the changes of unsubscribing rates for the three incentive strategies and compares the numbers of subscribers three months later from the actual data stored in December 2004.

  B) Operation evaluation by providers
  The provider introduced a new lottery incentive strategy that gave tokens to ten subscribers who gave fifteen correct answers. The provider compared the actual number of subscribers in the month when the new strategy was introduced

with the predicted number by the proposed tool, based on the previous month’s data.

Furthermore, in all experiments, forecasting method regarded the number of new subscribers as a fixed number.

4.2 Evaluation of the forecasting method

Using the actual data for August, the method forecasted the number of subscribers for the next three months and compared error with the actual data from September to November.

Table 1 shows the error and the degree of change in subscribers in each stage. The average of the absolute values of error for the number of subscribers in each stage after three months is 3.9%. The same value by the forecasting method of each segment using a contrastive method is 7.7%, confirming that forecasting by the proposed method is twice as precise as the contrastive method.

Table1. Forecasting precision of subscriber numbers (%)

M		All	Stage				E
			1	2	3	4	
1	A	-0.9	-1.2	-1.5	0.5	-0.5	0.9
	B	-1.7	0.8	-4.0	-0.5	-5.0	2.6
2	A	-1.2	-1.4	-3.9	1.6	0.6	1.9
	B	-2.7	2.4	-9.5	-1.0	-7.2	5.0
3	A	-1.1	1.3	-6.6	-4.8	2.8	3.9
	B	-4.6	2.1	-13.4	-8.3	-7.1	7.7

A: Proposed method that forecast each subscriber

B: Contractive method that forecast each segment

M: Month

E: Average error rate

4.3 Comparison of improvement strategies

For practical occasions, the provider considered a new lottery incentive strategy that gave prizes to ten subscribers who satisfied the conditions shown in Table 2. To examine which condition is the best, the proposed forecasting method was used.

Table2. Comparison of three incentive plans

Plan	Change of unsubscribing rate		Rate of increase		
	Change Condition	Rate	1 m	2 m	3 m
A	All	-30%	0.1	1.5	3.5
B	Less than 3 months	-50%	-0.8	0.3	1.4
	More than 4 months	0%			
C	Lower than stage 2	-20%	-0.4	0.7	1.6
	Higher than stage 3	-50%			

Target Condition

Plan A: All subscribers who gave 15 correct answers.

Plan B: Subscribers whose subscription periods are less than three months.

Plan C: Subscribers whose stages are higher than two.

As the results shown in Table 2, since plan A was the best, the provider instituted it. About the forecasting tool, the provider said that "because it can forecast the number of subscribers simply by inputting several parameters, it is useful to evaluate new improvement strategies."

4.4 Evaluation of operation by provider

In December, the provider informed all subscribers that a new incentive (Plan A in Table 2) would start the following month. The forecasting result a month later with the log data in December were compared with the actual data in January.

To examine the cancellation error, this experiment ignored new subscription error because such error in January was regarded as the difference between new subscribers in January and December. The error of the number of all subscribers is -0.1%, as shown in Table 3, and the error at each stage is from -5.0% to 1.9%.

Moreover, the forecasting results two and three months later were compared with the actual data in February and March. This forecasting method underestimated the number of all subscribers about 4% in February and 2.5% in March.

Table3. Error rate of numbers at each stage

	All	Stage			
		1	2	3	4
Error rate (%)	**-0.1**	**1.8**	**1.9**	**-1.4**	**-5.0**

5. CONCLUSION

This paper proposed a subscriber number forecasting tool for the providers of mobile quiz game contents that can evaluate new improvement strategies for prolonging subscription periods. Using the proposed tool, three improvement strategies were compared in a practical environment. Moreover, one of the strategies was enforced and the actual data of the number of subscribers were close to the forecasting results. Because the tool can forecast the number of subscribers using only attribute conditions and changes in the unsubscribing rate, the providers can easily use the tool to evaluate new improvement strategies.

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