A Study of Crucial Factors for In-App Purchase of Game Software

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Abstract. Google Play and App Store registered 17.2 billion downloads of game software worldwide in the first quarter of 2016, according to a report published by Sensor Tower, a platform that supports apps for iOS and Android. Related researchers too predicted tremendous growth in gaming applications. Not only the game App developers need to know how to design products that match gamer's needs, and will continue to use it, but also allure gamers to decide in-app purchase (IAP) which is the final goal. In particular, IAP is the major revenue model. Hence, this study attempts to define the potential factors influencing IAP for gamer. We collect data for many possible features from which, using Least Absolute Shrinkage and Selection Operator (LASSO) feature selection method, we identify important factors that affect gamer IAP behavior. The extracted factors can help game developers to improve their design for increasing revenue.

Keywords: Game app · Feature selection · Least Absolute Shrinkage and Selection Operator (LASSO) · In-app purchase (IAP)

1 Introduction

According to a fresh forecast from App Annie, game sales will hit 41.5 billion USD in 2016 and reach 74.6 billion USD by 2020 [1]. This Statistics Portal pointed out that the global mobile game revenue will reach 40.6 million U.S. dollars, up from 30.1 million in 2015 [39]. From the above, we can conclude that mobile game has become an important revenue earning application on a digital platform.

The App Monetization Strategies includes in-app advertising, in-app purchase, freemium, paywalls, paid apps, sponsorship [38] etc. An in-app purchase (IAP) is when the game is bought from within the application, typically a mobile app running on a smartphone or other mobile devices. Software vendors can sell all manners of things from within apps. In games, for example, users can buy characters, upgrade abilities and spend real money on in-game currencies [41].

Recently, related issues regarding revenue models of game app has also attracted the interest of researchers. For examples, Park and Kim [13] discussed

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the key successful factors of App. Koekkoek [14] discussed how successful apps make money from their user base. Roma and Ragaglia [29] empirically examine how the revenue model, adopted for a given app, affects the app revenue performance as measured by the app daily revenue rank. Gao et al. [23] discovered the continued use intension for mobile payments. Lin and Wang [15] aims to investigate the key factors underlying consumers' decision to buy Apps for their smartphones.

In recent years, many researchers hypothesized various factors that may affect IAP [3,6,7,9,16–18,22] etc. However, no previous studies have investigated which are the important factors, among all those proposed, that actually affect gamer IAP behavior [6]. In this highly dynamic and competitive environment [29], app developers need to know which factors are crucial to influence gamer's IAP [20]. This study examines a large number of potential factors as listed in Table 1, later in Sect. 4. The factors are from different works, and have overlapping meaning. It is easy to conclude that a few of them have strong correlations, and therefore it is possible to select some as important and discard others. There are various algorithms for feature selection, which we briefly reviewed in Sect. 2. In this work, we used Least Absolute Shrinkage and Selection Operator (LASSO) feature selection method to identify crucial factors. This is mainly because it is very efficient. The motivation of this work is to identify most important factors, so as to help game developers to design products that not only matches gamer's needs but also lead to higher in-app purchase (IAP).

2 Literature Review

2.1 Related Works

Gamasutra [11] and Sensor Tower [37] regularly report the sales and revenue earned by game softwares. Worldwide game software downloads and sales grew unabated. Hsu and Lin pointed the IAP have proven to be an effective monetization strategy for freemium apps [6]. All survey point that IAP has become the mainstream of revenue model for game apps. Understanding how to target people who will actually spend money on a title, and which features of a game software attract the user for IAP, is vital to success. [2] shows that 18 to 24 is the age group that spends the longest amount of time on mobile apps. [12] indicated that the majority of big spenders in Southeast Asia are teenagers while in China hardly teenagers spends money on purchasing games. There the biggest group of spenders are people around 30 years old. [27] also pointed that in smart phone gamers, the average age of gamers is 31 years old. Those between 21 to 25 years constitute 20%, 16 to 35 years old player population accounts for nearly 80% of the proportion. Therefore, we focus on 18 to 40 years old players which covers the whole age range of mobile gamers. The subjects of our experiment were chosen from different age groups as shown in Table 2.

2.2 Features Affecting On-Line Game Purchase

We surveyed a large number of works where the factors leading to IAP are proposed or hypothesized. Different factors and corresponding works are listed in Table 1. As they are unrelated works, many of the proposed factors have overlapping meaning and are correlated. Naturally, there is a scope for feature selection, to find important factors. To the best of our knowledge, there is no previous work done for selecting which factors are important.

As we are not sure what affects a gamer to make an in-application purchase decision, we started with all possible factors proposed in previous works. We started with 27 factors, detail of which are described in Table 1. Our target classification is user's decision, whether the user will do In-Application Purchase or not. We need to find the smallest set of features that would give the highest classification accuracy. As mentioned earlier, some features are correlated. Discarding one feature does not mean that that feature is unimportant for the classification task. It only means redundancy, as a similar correlated feature is included in the selected set of features. We aim to select the smallest set so that it would be easier for the designer to focus attention only to those features.

2.3 Feature Selection

In many practical applications with real data, due to the presence of noisy, irrelevant, or correlated features, feature selection is one the most important step before classification and data mining [26,30,33,35,42,43,45,46]. The basic aim is to remove redundant or irrelevant features (attributes) and thereby reduce the computational cost of training the classifier, improving classification accuracy. In addition, it would facilitate data visualization and data understanding, and improve classification accuracy (generalization) for unseen samples [42].

Feature selection method is classified into two approaches: Filter method and Wrapper method. In filter method, an individual feature is evaluated using statistical methods like Chi squared test, information gain or correlation coefficient score. Features are selected according to their scores. In wrapper method a model is used, and a subset of feature is evaluated using the model. The model could be anything, like a regression model, K-nearest neighbor, or a neural network. Searching for the optimum subset of features, could be heuristic, stochastic or forward-backward to add and remove features.

We used Least Absolute Shrinkage and Selection Operator (LASSO) feature selection method. Among existing feature selection algorithms, LASSO (Least Absolute Shrinkage and Selection Operator) is the most popular one [19,28] because of its efficiency, robustness and high accuracy performance [30]. As evaluation is by logistic regression, it is very fast. LASSO was introduced in [32] as a means of eliminating less informative variables in least squares multiple linear regression. It is a method of automatic variable selection which can select variable by shrinking the coefficient values and setting some equal to zero [10], for features to be eliminated. It has been widely used in many fields [36,40]. There are non-linear versions of Lasso [45]. Depending on the data, it will give as good or better result compared to linear version. For efficiency, in this work we used linear Lasso. We draw trace plot of coefficients for different features, varying the regularization parameter. From this plot, we manually fixed the value of regularization parameter, such that the number of non-zero coefficients are low (here 6) and MSE is also low.

For testing the classification result using the selected features, we used Support Vector Machine (SVM) as classifier. Basically, SVM is a linear classifier. Usually, the data is projected to a higher dimension, using a non-linear function like polynomial or radial-basis-function, so that in the transferred higher dimension the data is linearly separable. The non-linear transfer functions are called kernel functions. When the number of features and the total available data are large, we do not need (and it is computationally heavy) to transform the data to higher dimension using a non-linear kernel. In our experiment, the number of selected features is low, and the total data is not large. We used SVM with rbf kernel. It is known that non-linear SVM will work better or at least as good as linear SVM (direct data). If the data is linearly separable, the result using linear or non-linear SVM will be the same. For finding optimum kernel hyper-parameters we used grid-search method.

2.4 Data Structure

The data set consists of opinions from subjects, the details of which is in Sect. 4.2. For every feature, the subjects were to score them by a number from 1 to 5. Therefore, a sample consists of a 27 dimension feature vector, where all elements are numerical with values from 1 to 5. We had 361 valid responses, i.e., we had 361 samples in total.

3 Methodology

The employed approach involves 8 steps, as follows: define factors of game apps, design questionnaire, pre-test questionnaire, collect data, pre-process data, implement and run LASSO feature selection, build SVM classifier, evaluate results and make conclusions. The details of the procedure steps are explained as follows.

Step 1: Define factors of game Apps
Based on related works, we assembled all proposed potential factors of game Apps for doing In-App Purchase. We surveyed published works and defined them. Next, according to these defined factors, we go to the next step to design questionnaire for collecting data.

Step 2: Design questionnaire
We developed a set of questionnaire to estimate gamer's feeling about the level of importance for factors which will probably influence her/his in-App purchase behaviors. Briefly speaking, this questionnaire contains three parts.

- Part I: Basic information of the respondent (subject). The subject puts a score from 1 to 5 for each factor.
- Part II: The question items of different defined factors to estimate the importance levels for doing in-App purchase.

– Part III: Whether in-App purchase is done or not? In addition, we also collect information about the mode of payment as well as amount spent, though we do not use that information in our present work.

Step 3: Preliminary test
The original questionnaire is issued for preliminary testing (pretest). In this step, according to the feedbacks of respondents, we modify the questionnaire items. Then, we finalize and issue the questionnaire.

Step 4: Data collection
After pretesting, the modified questionnaire will be issued to gamers who have experiences of playing game Apps. The subjects complete the set of questionnaire over a month, as they play and purchase (or not purchase) a game software.

Step 5: Data pre-processing
The collected data is integrated [24] into a data set. For feature selection as well as classification, 5-fold cross validation is used. The part of the train data used for feature selection is also used for training the classifier, and the rest of the data used for testing.

Step 6: Implement LASSO feature selection
The LASSO (Least Absolute Shrinkage and Selection Operator) is a regression method that involves penalizing the absolute size of the regression coefficients. Let p is the number of factors, and N is the number of samples, y_i be the outcome of x_i. The objective is to solve

$$min_{\beta_0,\beta} \left[\frac{1}{N} \sum_{i=1}^{N} (y_i - \beta_0 - x_i^T \beta)^2 \right], \ subject\ to\ \sum_{j=1}^{p} |\beta_j| \leq \lambda \tag{1}$$

Here, λ is a free parameter that determines the amount of shrinkage.

Step 7: Train Support Vector Machine (SVM) classifier
To see the effectiveness of feature selection using different methods, we use the whole attribute set (without implementing feature selection) and reduced attribute set (implementing feature selection) to build classifier. Feature selection by LASSO, χ^2, and back-propagation network (BPN) are compared. A SVM classifier is trained for checking classification performance.

Step 8: Draw conclusions
Through analysis of the results of step 7, we will identify important factors of influencing in-App purchases for game Apps.

4 Experiments and Results

4.1 Defined Factors

The 27 potential factors influencing purchase of game software are shown in Table 1. Based on that, we design questionnaire, collect responses to finally filter important factors based on user responses.

Table 1. Potential factors influencing purchase of game apps.

No	Notation	Factors	Supports
1	VM	Value-for-money	[5]
2	SV	Social value	[5]
3	AR	App rating	[5,34]
4	S	Satisfaction	[3,5,8]
5	U	Unexpectedness	[21]
6	Con	Confirmation	[21]
7	Com	Compatibility	[7,24]
8	AI	Affective involvement	[22]
9	PU	Perceived usefulness	[6,8,44]
1	PE	Perceived enjoyment	[3,5,8,44]
1	PEU	Perceived ease of use	[8,31]
1	GG	Graphics	[13]
1	GA	Animation	[13]
1	GS	Sound	[13]
1	GSC	Scenario	[13]
1	GC	Character	[13]
1	GI	Innovative	[13]
1	V	Visibility	[4,9]
1	VOL	Voluntaries	[4,9]
2	RD	Result demon	[4,9]
2	T	Trial-ability	[4,7,9]
2	IM	Image	[4,9]
2	Mm	Mass media	[7]
2	IC	Interpersonal	[7]
2	Cc	Cognitive co	[44]
2	PR	Perceived ri	[17,25]
2	UC	Use context	[44]

4.2 Collected Data

A total of 410 responses of questionnaires were collected, 271 over the Internet and 139 in the paper-and-pencil version. After removing invalid responses, 361 valid responses are kept for further analysis.

Table 2 shows the basic information of subjects and collected samples (such as gender, age, and income per month of respondents). We gathered information about their background regarding operating system, game usage time per day, playing experience, game types, and payment methods. Finally, we could know only 27% respondents who did in-App purchase and the amount of in-App purchase is more than 5 USD (35%), and then 1 USD each time (27%).

Table 2. Statistics of collected data

Variable	Distribution
Gender	Male:56%, Female:44%
Age	<18 years old (3%) 18∼30 years old (46%) 31∼40 years old (17%) >40 years old,(34%)
Income per month	<5K NTD (24%) 5K∼10K NTD (10%) 10K∼20K NTD (13%) 20K∼50K NTD (39%) >50K NTD (14%)
Operating system	iOS (29%) Android (66%) Windows Phone (5%)
Game usage time per day	<3 hrs (70%) 4∼6 hrs (23%) 7∼9 hrs and above (7%)
Playing experience	<1 year (30%) 1∼3 years (33%) 3 years and above (37%)
Game types	Sports/Simulation/Driving (28%) RPG/MMORPG/Strategy (25%) Action/Adventure/Fighting (18%) Children/Educational (7%) Above (22%)
In-App purchase	Ever (32%) Never (68%)
Payment methods	Credit card (38%) Far Eas Tone Telecommunications (20%) Google play gift card (3%), PayPal (2%) Google wallet, (2%) ATM (7%) Point card (28%)
The amount of in App purchase	<1 USD (27%) 1∼1.99 USD (16%) 2∼5 USD (22%) >5 USD (35%)

In addition, data set [24] have 131 valid data. To compare with it, we make use of random repeat sampling on collected data to get the same quantity.

4.3 Results of Feature Selection

In this study, 5-fold cross-validation experiment is done. Those factors whose coefficient values are not zero are picked up as important factors. Results of LASSO feature selection method is shown in Table 3. Based on occurrence frequency, we can build the important feature set. The feature subset selected by LASSO is PEnjoy2, SV2, AI, GA, GSC, GI.

Next, we train SVM classifier to evaluate the effectiveness of LASSO and compare with original full feature set (without feature selection).

Table 3. Summary of selected factors (LASSO feature selection)

Fold	Factors					
	Fold1	Fold2	Fold3	Fold4	Fold5	Occurrence frequency
PEnjoy2	0.725	0.461	0.562	0.562	0.725	5
SV2	0.564	0.476	0.508	0.508	0.564	5
AI	0.224	0.159	0.183	0.182	0.224	5
GA	0.268	0.219	0.236	0.236	0.268	5
GSC	0.058	0.044	0.050	0.050	0.058	5
GI	0.329	0.322	0.327	0.328	0.329	5
IC1	0.038	0	0	0	0.038	2
PU1	0	0	0	0	0	0
PU2	0	0	0	0	0	0
PE1	0	0	0	0	0	0
PE2	0	0	0	0	0	0
C1	0	0	0	0	0	0
C2	0	0	0	0	0	0
V1	0	0	0	0	0	0
V2	0	0	0	0	0	0
RD1	0	0	0	0	0	0
RD2	0	0	0	0	0	0
VOL1	0	0	0	0	0	0
VOL2	0	0	0	0	0	0
T1	0	0	0	0	0	0
T2	0	0	0	0	0	0
I1	0	0	0	0	0	0
I2	0	0	0	0	0	0
PR1	0	0	0	0	0	0
PR2	0	0	0	0	0	0
PR3	0	0	0	0	0	0

Table 4, shows the results of SVM. In this table, we can see LASSO selected features show better performances compared to when all features are included in classification. Table 5 provides comparison of LASSO, BPN, and chi-square methods. From this table, we can find LASSO feature selection outperforms BPN and χ^2. Based on the results, we can claim that we found 6 important factors, as listed in Table 6. Due to strong correlation, it is possible that some other important factors are not included. By including that, and discarding one of the selected factor, it is possible to achieve similar classification results. But, our aim of getting minimum subset of features is achieved.

Table 4. Evaluation results of LASSO feature selection

Index	Factor set	
	Original set	LASSO set
	Mean (StDev)	Mean (StDev)
OA (%)	75.38 (8.85)	76.15 (6.88)
F1 (%)	77.22 (9.72)	78.19 (8.26)
Time (s)	0.50 (0.04)	0.24 (0.05)

Table 5. Comparison of LASSO and [24] feature selection methods

Index	Factor set		
	LASSO set 6 factors	[24] BPN set 4 factors	[24] χ^2 set 16 factors
	Mean (StDev)	Mean (StDev)	Mean (StDev)
OA (%)	76.15 (6.88)	64.62 (7.40)	61.54 (6.08)
F1 (%)	78.19 (8.26)	67.62 (6.41)	62.32 (10.43)
Time (s)	0.24 (0.05)	4.29 (2.01)	4.26 (3.45)

Table 6. The extracted important factors

No	Notation	Factors	Definitions
1	SV	Social value	The degree to which an app is perceived as the enhancement of a person's self-concept provided by the product
2	PE	Perceived enjoyment	The extent to which the activity of using the App is perceived to be enjoyable in its own right, apart from any performance consequences that may be anticipated
3	AI	Affective involvement	The expected that consumers who connect interactivity to mobile apps may believe that using mobile apps is appealing and interesting
4	GA	Animation	Movement of characters or background
5	GSC	Scenario	Creativity of the scenario
6	GI	Innovativeness	Newness of the game to the market

In order to further evaluate the effectiveness of LASSO, we also compare the performance of LASSO with the feature selection method of [24].

5 Conclusion

The purpose of this study is to determine crucial factors of influencing in-App purchase.

From available literatures and [24] data set, 27 potential factors have been defined. Further, we employ LASSO to select the important factors. Results indicated that LASSO can effectively recognize 6 crucial factors. They are social value (SV), perceived enjoyment (PE), affective involvement (AI), animation (GA), scenario (GSC), and innovativeness (GI).

Therefore, game App developers should pay their attention to these crucial factors which can increase their revenue. As future work, we plan to use other more powerful feature selection method to identify important factors of doing in-App purchase. Additionally, more data from more subjects need to be collected for more reliable results.

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