COUNTING CUSTOMERS IN MOBILE BUSINESS – THE CASE OF FREE TO PLAY

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Abstract

In recent years mobile games have become a major part of the mobile market since gaming apps generate a major amount of the platforms revenue. Whilst different business models have been used - free to play seems one of the most promising to monetize games in the mobile market. Yet, this new concept of monetizing digital content has not obtained much attention of researchers. One research gap is the prediction of users purchasing behavior, as it is a major challenge for practitioners as well as for researchers and of vital importance for managing marketing expenses and designing game mechanics. In this paper we use an existing prediction model for purchasing behavior to analyze its applicability in the mobile market. We use two data sets from free to play games to train and test this well-known model. We can show that existing models, even though they are designed for the same type of customer relationship, struggle with the case of free to play. We show detailed information on the model performance and conclude that because of the unique purchasing behavior in free to play models should be redesigned or the process of application should be more structured.

Keywords: Mobile games, mobile commerce, customer lifetime value, probability models, free to play

1 INTRODUCTION

Mobile games have become a major driver in the entertainment industry. Actual data shows that smartphone and tablet account for 29% of the global gaming market (Casual Games Association 2014). One recent radical change in the industry is a new way of monetizing the game content - called free to play. Free to play games mean that publishers give videogames away for free and appeal the gamers later whilst playing to buy virtual items (Guo & Barnes 2011). Yet, the user can still keep using the game without paying. Virtual items can for example increase the virtual character's ability or simply individualize the character with decorative items (Guo & Barnes 2011; Park & Lee 2011). The easy and free entry into the game courts a much larger base of customers. The number of games with a free to play revenue model, the user base, and generated revenue increase disproportionately worldwide (Casual Games Association 2014). The mobile gaming market experiences a huge shift towards free to play games (Lin & Sun 2011; Park & Lee 2011). As game professionals state that free to play seems the best choice for mobile games at the moment (Alha et al. 2014). Hence, the success of those games keeps calling for competitors and has led to an enormous amount of free to play games in the market. This decreases the potential user base a single game can attract, reduces the chance of retention and increases the cost for publishers to gain new users.

This challenge forces game developers and publishers to look for measurements to increase the games profitability. Therefore, it is important to them to identify their most profitable users. This leads to intensive usage of analytic methods in games management (Seif El-Nasr et al. 2013). The common concept to predict the potential value of customers is known as the customer lifetime value (CLV). This concept has been established in marketing research and is based on the expenses a company incurs to attract, sell and service the customers, and the revenue generated by them (Jain & Singh 2002). On important aspect of the CLV is to model the future purchases of a customer (Berger & Nasr 1998; Jain & Singh 2002; Romero et al. 2013). By now these models have mainly been built on business cases in medical offices, attorneys, insurance related firms, customer database, high-tech B2B, retail, and e-commerce (Romero et al. 2013). Yet, because research on games has shown that game mechanism influence the user behavior (Alha et al. 2014; Hamari & Lehdonvirta 2010), that the lifetime of gamers in a game is only within days (Sifa et al. 2014) or that frequent buyers in games tend to repurchase more likely (Hanner & Zarnekow 2015) it is an important aspect to reinvestigate the applicability of existing models.

Whilst the amount of available models is steadily increasing many of them have stayed in the academic world without much recognition of practitioners (Wuebben & Wangenheim 2008). The reasons might be manifold but certainly the complexity of most models seems a big hurdle for real world application (Fader et al. 2005a). Yet, some researchers have focused their model development to overcome that hurdle by reducing complexity of the model and ease the implementation. One of these models is the BG/NBD model of Fader et al. (2005a). It has been acknowledged for its ease of use and still accurate results and is the state-of-the-art approach to predict customer transactions (Guo et al. 2013; Jerath et al. 2011; Ma & Büschken 2011; Wuebben & Wangenheim 2008). Yet, research still lacks of empirical results by applying the models to real cases (Fader et al. 2005a; Wuebben & Wangenheim 2008). And as mentioned new types of purchasing behavior (e.g. free to play) have not been examined in the context of prediction models

This paper targets that research gap by two ways. It will test the BG/NBD (beta-geometric negative-binominal distribution) model for applicability in free to play and it will shed lights on purchasing behavior of free to play game customers by analyzing the outcome of real data and model prediction.

The paper is structured as follows. The second chapter *theoretical background* will explain common concepts in research regarding virtual items/free to play games and secondly the concept of customer behavior prediction models and the BG/NBD model. The third chapter will evaluate the model with two different data sets. Therefore, we will give information on our research design as well as the results of the analysis. In the fourth chapter we conduct a cross case analysis to evaluate differences and similarities between both cases and the general application of the model. The paper ends with a conclusion.

2 BACKGROUND

2.1 Free to play (mobile) games

Many games that enter the games market use this revenue model free to play and as mentioned in the mobile games market it is the majority. Recent studies show that the app-stores of Apple and Google depend heavily on the revenue of games as in both more than 75% of the stores revenue come from mobile games (International Data Corporation (IDC) 2014). In academic research free to play became more present just recently. Researchers analyzed the business models of the top 300 apps in the Apple app-store. Most of them are games and most of them use free-to-play as a revenue model (Brockmann et al. 2015). The way those games work is manifold and can differ in terms of user group, platform and genre. But, by now in most possible combinations there can be examples for games that use a free to play revenue model.

The revenue model free to play refers to selling virtual items for real money in a gaming environment (Guo & Barnes 2011). Research regarding virtual items covers user's motivation to buy them (Park & Lee 2011). A more economic perspective can be found e.g. in Gou and Barnes (2011) who investigated purchasing behavior in virtual worlds. As a result they can partly explain the users' intention to make an in-game purchase (Guo & Barnes 2011); a likewise approach can be found in the research of Mäntymäki and Salo (2013). More research was conducted on the intention to purchase virtual products by Animesh et al. (Animesh et al. 2013) or Hamari (2015). Wu et al. focused on explaining the business logic of online games. They showed similarities to two-sided markets and how network effects influences the games profitability (Wu et al. 2013).

Furthermore, scholars have explored the importance of game mechanics. For example, Lin and Sun explore the impact of virtual items on the fairness in games. I.e., what happens if gamers can buy an advantage in the game for real money (Lin & Sun 2011). Hamari and Lehdonvirta analyze how game design can foster the user's intention to buy virtual items (Hamari & Lehdonvirta 2010). Also the perspective of game mechanic and customer relationship has been analyzed by (Hamari & Järvinen 2011). In this context many researcher have analyzed the value of virtual items - a summary of research can be found in (Park & Lee 2011).

Mostly the user cannot buy a virtual item directly with real money. It can only be obtained through an in-game currency. Therefore, free to play games have two types of currency. One that can be earned within the game (e.g. resources like stones, iron etc.). The second type of currency "premium-currency" (e.g. diamonds) can sometimes be earned in the game but in most cases it has to be purchased with real money. This type of in-game currency is sold in packets. E.g. a user can buy 10 diamonds for $ 1,99 or 100 for $ 18,99. After the purchase, the user can use this currency to buy the wanted virtual items.

2.2 Customer behavior prediction models

The CLV is a widely discussed topic in the academic literature (Gupta et al. 2006). Due to closer customer relationships and progresses in technology the topic became interesting for researches as well as practitioners (Berger & Nasr 1998). Closer customer relationship refers to a direct contact between customers and firms due to new channels like the internet (Jain & Singh 2002). Progress in information technology means the feasibility to track the customer purchasing behavior (Berger & Nasr 1998; Gupta et al. 2006) making the transaction data available (Fader et al. 2005c). The CLV can be seen as a metric to assess the return of marketing investments (Gupta et al. 2006). Further, it allows a firm to identify the most profitable users on an empirical model. Therefore, the firm can foster an efficient allocation of marketing resources (Jain & Singh 2002). Besides a wide range of topics regarding the CLV, Jain and Singh summarized three areas of research (Jain & Singh 2002). Two of them focus on modeling and analyzing the customer base and their purchasing behavior. The calculation of the CLV takes all expenses into account whereas the customer base analysis analyzes the existing customer base to predict future transactions. The third area focuses on the effects of loyalty programs on the CLV and the firm's profitability (Jain & Singh 2002). Gupta et al. classify six different types of CLV models (see (Gupta et al. 2006) for further details). Whilst some of them are restricted to classification, several approaches focus on the prediction of customer behavior. The later used BG/NBD model belongs to the class of probability models (Gupta et al. 2006). This means that an "*observed behavior is viewed as the realization of underlying stochastic process governed by latent (unobserved) behavioral characteristics, which in turn vary across individuals"* (Gupta et al. 2006). This allows the model to reduce the complexity and come up with a generic, thus widely applicable model. Further, it can cover any time horizon, it is not needed to split a data set to be calibrated and it can cover specific purchasing behavior that other models struggle with (for details see Fader & Hardie 2009).

A major difference between these models, besides their class, is the type of customer relationship in which the model is developed. Fader and Hardie (2009) presented following typology to classify this relationship, see figure 1. This differentiation is necessary as it influence the basic assumptions in the used mathematical model. In noncontractual settings the churn of a customer cannot be observed directly. Thus, one can only guess about the relationship status by looking at observable values. The opportunities for transaction discerns between settings where a customer can only make purchases in given events (discrete) and settings where a customer could buy anytime (continuous) (Fader & Hardie 2009).

Opportunities for Transaction	Noncontractual	Contractual
Continuous	Grocery purchases Doctor-Visits **Free to play Games**	Credit card Student meal plan Mobile phone usage
Discrete	Event attendance Prescription refills Charity fund drives	Magazine subs Insurance policy Health club membership

Type of Relationship With Customers

Figure 1: Customer relationship (Fader & Hardie 2009)

In the case of free to play the users can purchase continuous (any time they want in the in-game store) and they do not have a contractual relationship to the publisher (they can leave the game anytime). Therefore the BG/NBD model should be usable as it is designed for that type of customer relationship.

2.3 BG/NBD Model

The BG/NBD model has been published by Fader et al. (2005a). It has been used in the context of continuous transactions and non-contractual settings. Originally the authors used the CD NOW data set that is publicly available (for further information on the data set see Fader & Hardie 2001). The BG/NBD model was developed on basis of the Pareto/NBD that has been presented by (Schmittlein et al. 1987). It is the first notable approach to use probability models in the context of customer purchasing behavior. Both share the buy-till-you-defect principle, hence, a customer is purchasing as long as she or he is active once inactive the customer will never purchase again (Fader et al. 2005a). Yet, it had several limitations that Fader et al. tried to overcome in their model. The Pareto/NBD model could only be implemented in MATLAB or other mathematical software. This is why researchers argue that the model is not workable enough. Therefore, it reduced the potential application in practice. Further, the BG/NBD reduced the amount of computational power and the complexity the software has to handle. Thus, it was possible to implement the model into Microsoft EXCEL (Fader et al. 2005a).

The basic principle of the BG/NBD model is that customers follow a certain pattern in their purchasing behavior that is characterized by underlying stochastic behavior. If it is possible to model the underlying behavior (by using distribution functions) one can make predictions about the future purchasing behavior (Fader et al. 2005a). Still, to get there one has to overcome several issues. The model must be able to be adjusted with existing data. Yet, the shape parameters of distribution function might not fit this data. This is overcome by modeling the individual as well the heterogeneity across customers by using mixed distribution. Again that allows calibrating the model on the total cohort of customers and then - by knowing their heterogeneity - a single customer can be picked out of that cohort. Due to the mixed distributions the data needed in the model is reduced to three necessary values ($X = x$, t, T) where $X = x$ is the number of purchases made in time frame $[0, T]$, with the last purchase occurring at time t, where $0 < t \leq T$ (Fader et al. 2005a). The model makes following assumptions about customer behavior (see Fader et al. 2005a).

- Individual level:
  - The purchasing rate is modeled with a Poisson process with purchase rate λ (this only applies if the customer is set as active).
  - The lifetime is modeled with the number of transactions according to a (shifted) geometric distribution with dropout probability p.
- Heterogeneity across customers:
  - The purchase rate λ for the different customers is distributed according to a gamma distribution across the population of customers.
  - The customers' dropout probabilities p for different customers is distributed according to a beta distribution across the customers.
  - The purchase rates λ and dropout probabilities p are distributed independently of each other.

The models mixed distribution shape parameters are r, α, s and b. If they are calibrated to the real data, the BG/NBD model can show the weekly and cumulative weekly repeated purchases for the total cohort of customers over the adjusted time period. Further, by using the shape parameters the model can predict a particular customer's future purchase based on her or his past behavior.

3 MODEL EVALUATION

3.1 Research design

In this section we want to give further details on the research design. That includes how we obtained the data and how we processed it for the application. We will show how we proceeded with the parameter estimation in the BG/NBD model and we will describe the measurements we did to evaluate the results of the model.

3.1.1 Data collection

The data is provided by a marketing firm in the videogames industry that chose to remain anonymous. The data comes from two different free to play mobile games, which are all released by different publishers. Both, games and publishers, have to remain anonymous.

These games have been chosen, firstly, to dispose of different genres for observation, secondly, because - according to the marketing firm - they performed differently in terms of profitability. The observed time period is from 08/15/2013 until the 03/07/2014. The information about the purchases is tracked by the back-end of the publishers' infrastructure. The users come from mostly European countries and the USA. The following figure shows the structure of the data of a generic paying user (see figure 2).

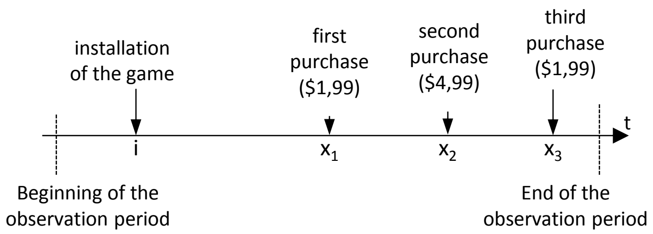

Figure 2: Data structure

The data tracking starts with the installation process of the game. During this process, every user is tracked with its own ID that can be related to any purchase this single user does during his or her customer lifetime. The information about those purchasing events includes the amount spent (a fixed price for a packet) and the timestamp (day/month/year/hour/minute/second).

3.1.2 Data preparation

The data includes only customers that have at least made one purchase in the game. The lifetime of a customer is defined as the time between his or her first purchase and the last observable one. The cohort is defined by a timescale when they did their first purchase in the game (see figure 3). We follow the method of Fader et al. who use the customer cohort that made a first purchase in the first 11.86 weeks in their data sample from CD NOW. That is around 14.5% of the total observation time. They split their observation period in half one for the calibration and one for the prediction. This means for us that we use the first four weeks to define our cohort of users, whilst splitting the observation period in week 0-14 and week 15-29.

It can be seen that our data differs regarding the length of time. We still feel confident that in the case of free to play the period of time we use is sufficient to cover most of the customers' lifetime. Furthermore, it is argued that probability models are not sensitive to the periods of time (Fader & Hardie 2009).

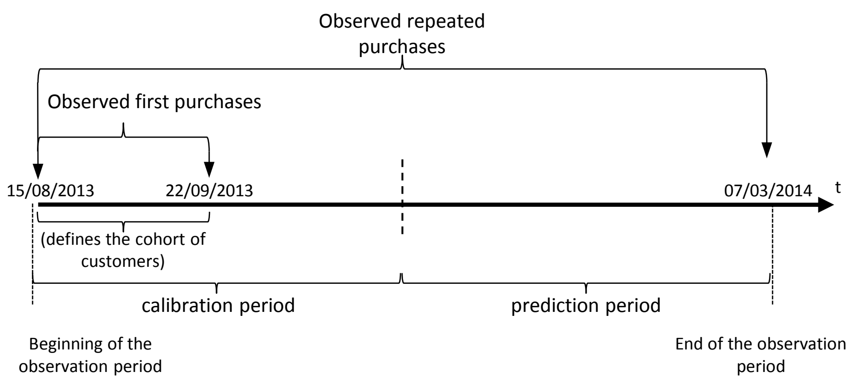

Figure 3: Cohort building

The model training follows the instruction of the (Fader et al. 2005a). We split the data into two half both with a length of 14 weeks. We define the cohort of customers as the customers that started purchasing within 4 weeks of the game that is 1/10 of the total observation period and in that regard the same percentage as the cohort used by Fader et al. (2005b).

For individual estimations we use the same time horizon we have for our real data. Hence, we predict it for 14 weeks. This is a measure that is needed by the BG/NBD model as the length of the prediction period must be given.

3.1.3 Model implementation and Parameter Estimation

The model is implemented as proposed by (Fader et al. 2005a). Further details are given in (Fader et al. 2005b). As mentioned in section 2.3 we need to estimate the parameters for the model. This is done by maximizing a likelihood function. The first 14 weeks of the data sets are used for the parameter estimation. We use the same method for parameter estimation as (Fader et al. 2005a) for their BG/NBD model. It is a standard numerical optimization method that is provided by the Solver tool in Microsoft EXCEL. We use the same log likelihood estimation as Fader et al. (2005b) and optimize the four different parameters by using different starting values (from 0,1 to 1) and re-do the parameter estimation until we reach stable values. For both cases the procedure resulted in stable parameter values. Yet, it should be noted that the parameter estimation by using more accurate numerical optimization methods like MATLAB could lead to better results. But as tested by Fader et al. the results did not differ. Following table presents the results for parameter estimation and the resulting likelihood function for both data sets.

Table 1: Results of Parameter Estimation and Log Likelyhood

Parameters and LL	Set A	Set B
r	0.371	0.512
α	0.399	0.823
s	1.431	0.703
b	3.495	8.108
LL	-970.3	-1,568.7

3.1.4 Measurements for analysis

For the analysis we use several different measurements. All of the measurements have been used by researches in the context of prediction models e.g. (Fader et al. 2005a; Jerath et al. 2011; Schmittlein et al. 1987; Wuebben & Wangenheim 2008).

One will be the direct comparison of the repeat purchases per week for the real as well as the predicted data. This allows us to understand how well the model can cover the adjustment to the real purchasing behavior of the total cohort of customers in the calibration as well as in the prediction period.

On the individual level the predicted number of repeated transactions per customer can be used as an indicator of the models performance. This will be calculated for the prediction period. Hence, we count the number of users for expected and real number of transactions in our predicting period week 15 to 29. This can be seen as classes of customers e.g. the customers that will never repurchase or the customers what will continue buying heavily (+7 more purchases in the prediction period). Thus, it allows us to examine how well the model can predict active customers and how well it is able to cover that segmentation of different customer classes.

To add more insights into the model results we will evaluate the model outcome and the condition for churned and non-churned users. Hence, this allows us to see if the model generally can predict churned customers, but more important it also allows us to see if still active customers have been classified as inactive.

Further, we will use the mean average error (MAE) to evaluate how well the model can generally predict customers purchasing behaviour be comparing the real and predicted repeated transaction for week 15 to 29 for every customer.

3.2 Model application

3.2.1 Data Set A

Data Set A comes from a game that can be seen as a resource management game (RMG) this means the user has to build and manage a virtual environment. The bigger this environment gets the more resources can be produced. This increases the user's level and global power. In this case user can buy a secondary in-game currency in different packet sizes. The size reaches from 0,99$ up to 89$.

Table 2: Statistics on Data Set A

Number of paying users	216
Average lifetime	4.18 days
Number of users with rep. purchases	146
Average number of purchases per user	4.13

Firstly, we look at the results for the whole cohort of customers. We can notice that the number of rep. purchases will increase within the first five weeks since new customers are coming in. Looking at the model data it can be seen that the model is not able to reproduce that fast increase. Since the average lifetime of a user is very short and the number of repeat purchases is around 4 the decline of purchases of the cohort is very rapid leading to only around 20 repeat purchases per day after the ninth week. This decline is not totally covered by the model, but it gets closer to the real repeated purchases in the predictive period. Whilst the analyzed cohort almost stopped purchasing at the end of the 29th week, the model still expects repeat purchases. By looking at the cumulated purchases it results in an underestimation in the beginning and an overestimation in the prediction period. The model expects repeat purchases up to the 72th week.

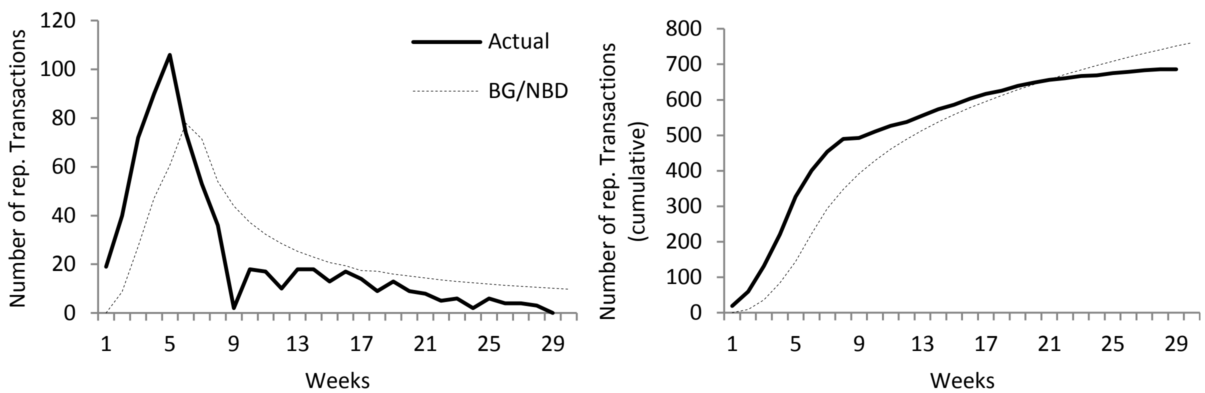

Figure 4: Predicted Versus Actual Weekly and Cumulative Weekly Repeat Transactions

On the individual level the real data shows, that after the calibration period most of the users will not ever make a repeat purchase. The model is able to cover that mostly correct as shown in table 3. On the other side the different classes that still repurchase have not been predicted correctly in most cases. It should be noticed the heavy purchaser class (7 or more repeat purchases) has was still predicted by the model. The MAE is 0.66. Hence, on average the model performs quite well, but if the big amounts of users that have been correctly classified as churned are taken into account the accuracy is not the best.

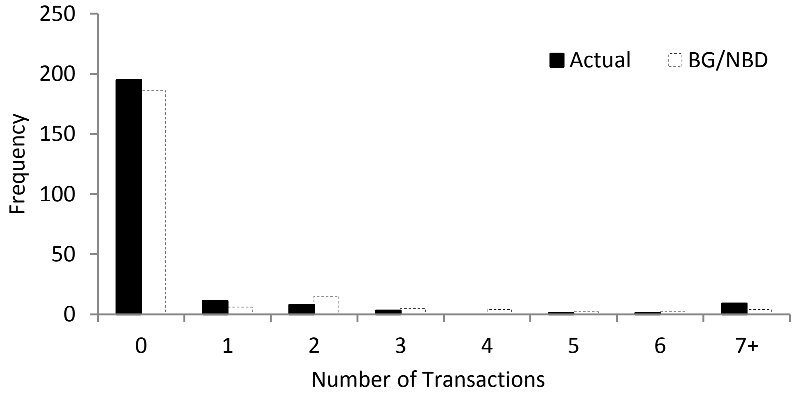

Figure 5: Predicted Versus Actual Frequency of Repeat Transactions

This is supported by the analysis of the condition for churned and non-churned users. As mentioned the churned users mostly have been classified correctly. Yet, the model tends to underestimate still active customers heavily. It should be considered that only a small amount of users is in that class.

Table 3: Condition for Classified Customers

Classified	correctly	incorrectly
Pred. Churned customer	88.21%	11.79%
Pred. Non-churned cust.	51.72%	48.28%

3.2.2 Data Set B

The second game is a sports management game (SMG). The user has the role of a sports club manager and is responsible for the sporting and economic future of the club. Like case A users can buy a secondary in-game currency in different packet sizes. The size reaches from 0,99$ up to 99$.

Table 4: Statistics on Data Set A

Number of paying users	224
Average lifetime	9.79 days
Number of users with rep. purchases	161
Average number of purchases per user	8.24

In this set we can observe a longer lifetime of customers and more frequent repeated purchases. The model is more able to cover that during the calibration period though, the real data has frequent peeks that can be related to special sales offers in the store. These peeks cannot be covered by the model, but this is unsurprising. Yet, they also lead to an overestimation. This becomes more severe in the prediction period. The model does not follow the declining repeat purchases and overestimates the repeated purchases during the end of the prediction period and the following weeks.

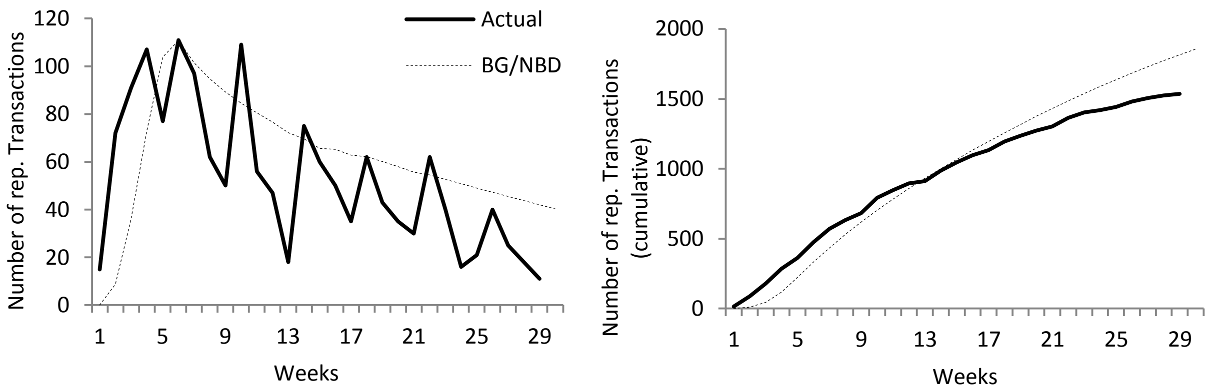

Figure 6: Predicted Versus Actual Weekly and Cumulative Weekly Repeat Transactions

On the individual level the class of churned customers has not been classified correctly. The model underestimates the churned customers thus it overestimates the repeat purchase. The high amount of heavy spenders still can be predicted by the model. Still, it has problems to classify other classes between 1 and 6 repeat purchases. The MAE is 2. This should be seen in the context of a higher purchasing rate and a bigger amount of still active users.

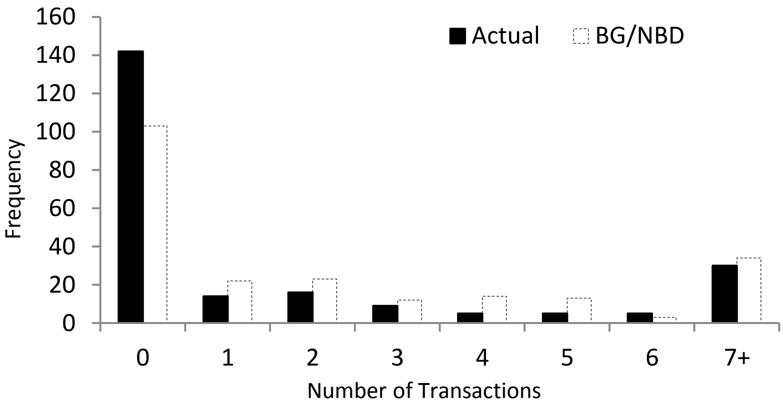

Figure 7: Predicted Versus Actual Frequency of Repeat Transactions

The classification of predicted churned and non-churned customers underlines the previous observation of correctly classified heavy users and also the underestimated churned users.

Table 5: Condition for Classified Customers

Classified	correctly	incorrectly
Pred. Churned customer	66.90%	33.10%
Pred. Non-churned cust.	90.22%	9.76%

4 CROSS CASE ANALYSIS

In both cases the calibration does not completely fit to the real data. But a first insight shows that the performance of the model differs between the two data sets. Data set A shows a volatile purchasing behavior in the first weeks, hence, during the calibration period. The number of new customers is pushing the repeated purchases in the first weeks, but the game seems to have a lack of stickiness and users do not keep purchasing for a long time. This again leads the model to overestimate the prediction period. Here we can observe a major difference between both games. Whilst game A declines heavily within the calibration period the model can cover that decline. In game B where customers stick longer to the game and have a higher rate of repurchases the calibration period adjusts the model to a very slow decreasing amount of repeated purchases per week. In this case the model overestimates the rep. purchase after the 29th week. Hence, we argue that the model is both sensitive to extreme events that happen in the prediction period and in the calibration period. It shows that the range of the mixed distributions is limiting the adaptability to real data. This does not seem surprising, but it will become a challenge if such models are applied in scenarios with fast increasing and declining repeat purchases especially in the prediction period.

Regarding the results from the class prediction the model performs different in both sets. Whilst for set A the accuracy for churned customers is good (88.21% correct) the model is not resulting in good predictions for set B (66.90% correct). This can be explained by the shorter average lifetime of 4.1 days in set A. Hence, because the prediction period starts in week 15 most users will have already stopped purchasing for a longer time. This makes it easier for the model to estimate churned customers, as the time since the last purchase (x) is the strongest indicator for the churn of customers. In set B users are more likely to be active right before the calibration period is ending. This leads to an underestimation of churned customers which is very critical for the model results. On the other side the strong overestimation of repeated purchases in set B lead to a good estimation of still active customers, yet, still restricted by not predicting churn correctly. Overall it shows that in situations where most of the users have churned for a long time before the prediction period starts the models does not have a better performance if wrongly classified active users are taken into account. This dilemma might be overcome by redesigning the model or optimizing the time for the calibration and prediction period.

Coming from the perspective of overall performance the already raised question from (Wuebben & Wangenheim 2008) seems important. Can such a model outperform simple heuristics? Though we did not test any heuristics the question also is valid in our case. If we look at the condition for customer classes in both data sets, the estimation is not accurate which is supported by the MAE. It could be said that rather good guesses could lead to similar results (Wuebben & Wangenheim 2008). Interesting to see is that the prediction of heavy users - especially in data set B - worked well. This is important, as heavy users generate a major part of the games revenue.

Regarding the models usability we would support the approach of (Fader et al. 2005a) as it reduces the complexity to a minimum. The implementation using EXCEL is straightforward and can produce valid results in both cases, yet, with already mentioned limitations. This allows an automation that simple heuristics could not achieve. This is a major advantage of probability models and supports their usefulness in a business context.

5 CONCLUSION AND FURTHER RESEARCH

In this paper we evaluate the possibility of existing purchasing behavior prediction models in free to play games. We showed that from a theoretical point of view, the BG/NBD model should be able to cover the case of free to play. As it is a comparable customer relationship as the one the model was originally designed for.

Within our model evaluation we used two different data sets from real games to test the model. The analysis showed that the model struggle with covering the real data. Already during the calibration period the model could not be adjusted to the real data. The differences became clearer during the prediction period where the model overestimated the weekly sales in both data sets. The prediction of different types of classes could not be covered by the model, but important factors like customer churn or heavy re-buyers could be partly classified correctly. And application of the BG/NBD model seems possibly in free to play games management.

In conclusion, we would argue that the unique behavior of customers in free to play games (short lifetime, high mount of repeat purchases and high heterogeneity across customers) make the application of existing probability models like the BG/NBD elaborate. But with accurate calibration it can be used as a fast and straightforward approach to predict and classify customers.

Our results should be considered with following limitations. We only used the BG/NBD model but besides this model several other authors have published approaches and models that could overcome some model given restrictions. Yet, to our knowledge the BG/NBD is the only model that allowed an easy implementation. We used only two data sets but existing research is also limited to only a few cases where actual data about customer behavior exists. Furthermore, the time period of the data is limited. It is likely that not all behavior is covered within this timeframe.

To follow our conclusion we would suggest future research to complement and extend this work. One way can be the redesign or adjustment of existing models. This would require re-examining of the basic assumptions of the Pareto/NBD or the BG/NBD regarding customer churn or purchasing behavior. Further, there is no extension of the BG/NBD model regarding the monetary value of customers this would be a fruitful contribution to the field. The other way would be further research regarding the implementation in a business context - especially in data driven business like free to play. Research could lead to interesting results for managers how to use such models what has to be considered regarding the implementation and results. This could also increase the usage of elegant probability models instead of only data mining algorithm and machine learning.

REFERENCES

Alha K, Koskinen E, Paavilainen J, Hamari J, Kinnunen J (2014) Free-to-Play Games: Professionals' Perspectives. In: Proceedings of Nordic DiGRA.

Animesh A, Pinsonneault A, Yang S, Oh W (2013) An Odyssey into Virtual Worlds: Exploring The Impacts of Technological and Spatial Environments on Intention to Purchase Virtual Products. MIS Quarterly 35(3):789–810.

Berger PD, Nasr NI (1998) Customer Lifetime Value: Marketing Models and Applications. Journal of Interactive Marketing 12(1):17–30.

Brockmann T, Stieglitz S, Cvetkovic A (2015) Prevalent Business Models for the Apple App Store. In: Wirtschaftsinformatik.

Casual Games Association (2014) Towards The Global Games Market in 2017: A broad look at market growth by screen & region.

Fader PS, Hardie BGS (2001) Forecasting Repeat Sales at CDNOW: A Case Study. Interfaces 31(3):S94-S107.

Fader PS, Hardie BGS (2009) Probability Models for Customer-Base Analysis. Journal of Interactive Marketing 23(1):61–69.

Fader PS, Hardie BGS, Lee KL (2005a) "Counting Your Customers" the Easy Way: An Alternative to the Pareto/NBD Model. Marketing Science 24(2):275–284.

Fader PS, Hardie BGS, Lee KL (2005b) Implementing the BG/NBD Model for Customer Base Analysis in Excel.

Fader PS, Hardie BGS, Lee KL (2005c) RFM and CLV: Using Iso-Value Curves for Customer Base Analysis. Journal of Marketing Research (JMR) 42(4):415–430.

Guo Y, Barnes S (2011) Purchase Behavior in Virtual Worlds: An Empirical Investigation in Second Life. Information & Management 48(7):303–312.

Guo Y, Wang H, Liu W (2013) Improved Pareto/NBD Model and Its Applications in Customer Segmentation based on Personal Information Combination. International Journal of Database Theory and Application 6(5):175–186.

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(2):139–155.

Hamari J (2015) Why do people buy virtual goods? Attitude toward virtual good purchases versus game enjoyment. International Journal of Information Management 35(3):299–308.

Hamari J, Järvinen A (2011) Building Customer Relationship through Game Mechanics in Social Games. In: Cruz-Cunha M, Carvalho V, Tavares P (Hrsg) Business, Technological and Social Dimensions of Computer Games: Multidisciplinary Developments. Hershey, PA: IGI Global.

Hamari J, Lehdonvirta V (2010) Game Design as Marketing: How Game Mechanics Create Demand for Virtual Goods. International Journal of Business Science & Applied Management 5(1):14–29.

Hanner N, Zarnekow R (2015) Purchasing Behavior in Free to Play Games: Concepts and Empirical Validation. In: 48th Hawaii International Conference on System Sciences.

International Data Corporation (IDC) (2014) Portable Gaming Spotlight.

Jain D, Singh SS (2002) Customer Lifetime Value Research in Marketing: A Review and Future Directions. Journal of Interactive Marketing 16(2):34–46.

Jerath K, Fader PS, Hardie BGS (2011) New Perspectives on Customer "Death" Using a Generalization of the Pareto/NBD Model. Marketing Science 30(5):866–880.

Lin H, Sun C (2011) Cash Trade in Free-to-Play Online Games. Games and Culture 6(3):270–287.

Ma S, Büschken J (2011) Counting your customers from an "always a share" perspective. Marketing Letters 22(3):243–257.

Mäntymäki M, Salo J (2013) Purchasing Behavior in Social Virtual Worlds: An Examination of Habbo Hotel. International Journal of Information Management 33(2):282–290.

Park B, Lee KC (2011) Exploring the Value of Purchasing Online Game Items. Computers in Human Behavior 27(6):2178–2185.

Romero J, van der Lans R, Wierenga B (2013) A Partially Hidden Markov Model of Customer Dynamics for CLV Measurement. Journal of Interactive Marketing 27(3):185–208.

Schmittlein DC, Morrison DG, Colombo R (1987) Counting Your Customers: Who Are They and What Will They Do Next? Management Science 33(1):1–24.

Seif El-Nasr M, Drachen A, Canossa A (2013) Game Analytics. Springer London, London.

Sifa R, Bauckhage C, Drachen A (2014) The Playtime Principle: Large-scale cross-games interest modeling. In: IEEE (Hrsg) Computational Intelligence and Games (CIG).

Wu C, Chen Y, Cho Y (2013) Nested Network Effects in Online Free Games with Accessory Selling. Journal of Interactive Marketing 27(3).

Wuebben M, Wangenheim FV (2008) Instant Customer Base Analysis: Managerial Heuristics Often "Get It Right". Journal of Marketing 72(3):82–93.