Predicting Daily Active Users for Match-3 Mobile Games

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ABSTRACT

We present in this paper a technique to attempt to predict the amount of daily active users for a match-3 mobile game by considering several factors that drives a game's social virality. The data was extracted from the performance of two match-3 mobile games by Playlab Inc., Jungle Cubes and Dragon Cubes. In this paper, we describe our experiments on these two games and the outcomes of the prediction model extracted.

Keywords

Data Mining, Classification, Regression, Daily Active Users, Mobile Games, Free-to-play, Retention.

1. INTRODUCTION

Free-to-play mobile games follow a common business model. It is a necessity that these games have a healthy community to drive the virality of the game. One of the key measures for determining the success of a mobile game is by using Daily Active Users (DAU) as a metric. This refers to the total amount of unique users who spent considerable time in the game given a certain date. This refers to the "stickiness" of the application. A high value for DAU indicates that there is much activity and demand for the mobile game. It is essential for game development companies that develop mobile games that follows a free-to-play model, to keep the DAU value as high as possible. This paper attempts to predict DAU value for two commercial match-3 mobile games, Jungle Cubes and Dragon Cubes, that are currently owned by Playlab Inc.

Companies that follow a free-to-play business model use various analytics tools to track user's behavior and events triggered in their applications. In this study, Playlab Inc., uses Flurry Analytics and Google Play Developer Console to collect user data. One of the attributes capable of being tracked is the DAU.

In this study, we present a hypothesis that the DAU value is driven by other attributes or events that causes a user to use the application (or in this case, play for a considerable time) extensively. Such attributes considered are discussed in the succeeding sections.

Business decisions for a mobile game are executed when there is sufficient user data collected. One of the major problems encountered by companies such as Playlab Inc., is that major releases for the game don't immediately provide significant user data. It would be appropriate to provide a forecasting technique to determine if there would be a significant user activity on succeeding days. In a practical scenario, this paper aims to answer the question; given a certain day with these collected attributes, how high will the DAU value be X days after? In our experiments, we specifically attempt to predict the Daily Active Users value at Day 7.

2. SIGNIFICANCE OF THE STUDY

Behavioral analytics has recently emerged as a practice for commercial game development. These also relates to technological advancements brought about by mobile devices that enable developers to gather more significant data through the use of commercial analytics.

There is a significant increase on the number of games that are shifting to the free-to-play (F2P) model and this study are one of the few instances wherein commercial game dataset are used for academic research. Findings will be beneficial for game companies that strictly complies with the F2P model. In specific, those who greatly rely on high user activity for their games will strongly find this paper beneficial for their business decisions.

We present a novel approach on how analysts or developers may attempt to predict the DAU value on a practical scenario, based from the formula given by our prediction model. We also attempt to define features that are highly important based from our analysis of attributes on our dataset and as supported by other similar study as seen in [3].

In this manner, we present the following contributions in this paper: We formally define from related study, as well as our findings, the attributes that affects the DAU value. We attempt to create several prediction models for the DAU value using machine learning techniques and explain its significance on a practical setting. We present a simple method on how one can predict the DAU value This paper are one of the few research study that uses dataset from commercial games which is otherwise, confidential and unavailable for academic research. Despite a small number of installs for both games, Jungle Cubes have very strongly correlated attributes against DAU, which make the dataset significant. We present this in detail in the succeeding sections.

2.1 Related Work

Using game analytics for research purposes has recently been pursued around 2012. Analysis of user behavior in digital games has become a fundamental practice for game companies. It is also open for numerous research opportunities due to its complex nature of modelling users while also taking into consideration the elements of the game. Thus, datasets concerning player behavior can be exceptionally complex like seen in World of Warcraft, a famous MMORPG (Massively Multiplayer Online Role-Playing Game), which has lead a team of researchers attempt to cluster players based from behavioral telemetry [2]. They applied numerous unsupervised learning methods to discover clusters of "player groups" based from their playtime data and their levelling pace.

2.1.1 Determining How Players Lose Interest

A study on action and shooter games released on Playstation 3, that uses player behavior dataset, have been used to discover how players lose interest in playing a game [1]. The dataset presented in their research paper were extracted from two single-player games (Just Cause 2, Tomb Raider: Underworld) and three multi-player games (Battlefield Bad Company 2, Medal of Honor, Crysis 2). All datasets have been sampled using simple random sampling or extraction of data on a timeline where player activities are high or the game was newly released.

The interest of playing a game cannot be measured directly but can be inferred from observable data as mentioned by [1]. In reality, a player's urge to play a game is influenced by several factors that appears as unforeseeable events to the analysts involved. This ranges from variance in playing schedules, personal satisfaction, release of new game content, or new games that competes with the player's attention. Using these consideration as mentioned by [1], they modeled the player's interest in playing a game as a random process. That is, at any given time, a player's interest is a random quantity that may or may not depend on previous values and future values cannot be predicted exactly. Thus, they have restricted their mathematical models to random process models; the Gamma distribution, Weibull distribution, Inverse Gaussian distribution, and Log-normal distribution.

Of all five games analyzed, researchers deduced that the total playing times follows the Weibull distribution. Following the Weibull model, it gives a good benchmark for gaming companies to determine how a player's playtime even before the game has been released.

2.1.2 Predicting Churn Rate

There is an existing research work that is highly related to our methodology. Researchers attempted to predict the Churn Rate of commercial mobile games which also uses some attributes we use for this study [3]. In their study, they threat the churn value as a binary classification task, a player is labelled as **churned** or **returning**. Given a specified *cutoff date*, the player will be labelled as **churned** or **returning** based from two formal problems defined in their study.

They described problem **P1** to be more straightforward. Given a cutoff date, players who did not return after the cutoff date are immediately considered as churners. The green dots in 1 are considered as **churners** while the red dots are players who managed to return after the specified cutoff date. This formal definition of churn is harsh and not useful for real-world applications. Problem **P2** is more relaxed. Given a grace period after the specified cutoff date, if players return during this period, they are considered as "about to churn" wherein their engagement to the game is already low. These are the players who are likely to quit soon and knowing how much players are inside this grace period aids gaming companies on potentially rescuing these players to get back to the game. In 1, the first two green dots refer to players already churned while the third green dot inside the grace period is flagged as "about to churn." The red dot is a player who managed to return to the game after the grace period.

Figure 1 shows an illustration of formal problem **P1** and problem **P2**.

- Feature Selection
  Attributes were universal and game-content independent. The following attributes stood out based from their feature selection tests and obvious observations that affect churning behavior; **Number of Sessions**, **Number of Days**, **Current Absence Time**, **Playtime per Session**, and **Average Time Between Sessions** and **Predefined Spending Category**. Some of these attributes are observed in our study.
- Experiments and Results
  In their research work, the most accurate classifier is the decision tree, among other different classifiers; neural networks, logistic regression, and naive bayes. F1-score goes as high as 0.916 for the decision tree model. We will also be using decision trees for our prediction since it has achieved a high accuracy from this study.

3. DATASET AND INFORMATION ABOUT ATTRIBUTES

This section contains an overview of the dataset used for this paper. The manner of extraction is also discussed in this section. Attributes are defined as well.

There are two datasets available for research and both are considered for the empirical study. The DNC Dataset and the JNC Dataset. Both datasets have been compiled and retrieved from Flurry Analytics, a commercial analytics tool used by Playlab Inc to track user's behavior on their commercial mobile games. Some attributes were retrieved from Google Play Developer Console such as user's ratings and daily crash reports. The DNC dataset refers to the Dragon Cubes game while the JNC dataset refers to the Jungle Cubes game. Both dataset are restricted to Android platforms only.

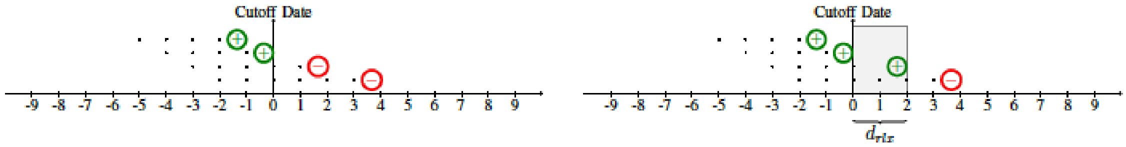

Figure 1: Formal problems defined as P1 and P2 described by [3]. P1 defines users as churners if they do not return after the specified cutoff date. In P2, players are given a grace period after the cutoff date. If players did not return after the specified grace period, they are considered as churners.

Table 1: Overview of Dataset Used

Dataset Filename	Game Title	Total Down-loads	Over-all Rating	Timeline of Dataset
DNC Dataset Android 0511-0911	 Dragon Cubes	50,000 - 100,000	4.2 out of 5	May 11, 2015 - September 11, 2015
JNC Dataset Android 0511-0911	 Jungle Cubes	100,000 - 500,000	4.3 out of 5	May 11, 2015 - September 11, 2015

Table 1 shows the overview of the datasets used for the study.

Both datasets spans on a similar timeline, that is May 11 - September 11,2015. A span of four months have been deemed sufficient for analysis and increasing the timespan no longer yields better results.

4. ATTRIBUTE INFORMATION

This section discusses the attributes used for this study. **??** contains the definition of attributes found in the dataset. These attributes have been gathered and selected from Flurry Analytics and Google Play Developer Console.

The initial selection of dataset has been manually performed by the researchers which they have deemed sufficient for analysis and have potential impact to the DAU value. On the succeeding section, we analyzed each variable and their correlation values to determine which variables have high relationship with the DAU value.

- Install Date - Each instance in the dataset is organized by install date. This refers to the gregorian calendar date wherein an application is installed.
- Cohort Size - Refers to the total amount of users who have installed the application on the given install date.
- Day X - This represents the retention of the application given a certain date and cohort size. Installation date becomes day 0. Retention rate is the percentage of returning users on a specified install date. For example, day 1 has 40.75% retention and 1200 cohort size. Therefore, 40.75% of users have managed to return on day 1 (489 users in cohort size)
- CrashesANRDay1 - reality, crash reports come in a day after the specified install date. For example, May 11,2015 has 3 crash reports. This means that this value was only retrieved on May 12, 2015.This counts the total number of crashes and ANRs (application not responding) reports from the application. This has a negative impact for the user experience. In reality, crash reports come in a day after the specified install date. For example, May 11,2015 has 3 crash reports. This means that this value was only retrieved on May 12, 2015.
- DailyAverageRating - This refers to the average rating by users who choose to rate the application (1 to 5, 5 being the highest) on a given date. Rating an application is not mandatory. This is a primary determination for virality. Similar to CrashesANRDay1, the tally comes in a day after the specified install date.
- LevelPlayedEvents - Refers to the accumulated event tally that is triggered when a user plays a level on the application. This is triggered upon tap of the 'Play' button. This event is reported no matter the outcome of the level being played.
- LevelSuccessEvents - Refers to the accumulated events that are triggered if a user successfully completes a level. This is triggered when the 'Win' screen is shown to the user.
- LevelFailedEvents - Refers to the accumulated events that are triggered if a user fails a level. This is triggered when the 'Lose' screen is shown to the user.
- Session - Refers to the total amount of play sessions on a given install date. A high value for session count on a given install date means that there are a lot of playthrough activity
- MKTExpenses - This is the total amount of marketing expenses, in USD, spent to advertise the game. Given an install date, the marketing expense normally determines the cohort size. A high marketing expense means more advertising channels have been used to target more potential users to install the game.
- ActiveUsers - This refers to the total amount of unique users who spent considerable time in the game given a certain date. This refers to the "stickiness" of the application.This is one of the attributes essential for determining a game's success.

- ActiveUsersDay7 - This is similar to the ActiveUsers variable but offset 7 days after the install date. This is the variable to be predicted.

In reality, given a install date, and one would like to know how many daily active users would there be 7 days after, the following variables will be used: Cohort Size, Day 1, CrashesANRDay1, DailyAverageRating, LevelPlayedEvents, LevelSuccessEvents, LevelFailedEvents, Sessions, MKTExpenses, and ActiveUsers.

Note that some variables like DailyAverageRating and CrashesANRDay1, only becomes available a day after. In a practical scenario, one could make predictions by Day 2 since it is assumed that all variables are readily available.

5. METHODOLOGY AND CLASSIFICATION TECHNIQUES

This section contains the methodology and different classification techniques used to predict the value **DAU-Day7** from two datasets, JNC and DNC.

On the business point of view, Jungle Cubes is a fairly successful game released commercially by Playlab Inc. due to its constant revenue despite having a small amount of users playing the game. On the other hand, Dragon Cubes have fairly considerable marketing expenses but did not reach the company's overall vision for the game. It also has seemingly random patterns as described by the marketing team. Here in this section, we attempt to uncover the plausible reason for this kind of outcome based from the dataset.

6. ACKNOWLEDGMENTS

7. REFERENCES

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