Deepening the understanding of mobile game success

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Abstract

It is increasingly difficult for game developers to build a mobile game that achieves the top positions on app store charts. There is currently no clear strategy to build successful games. In this context, the main purpose of our work is to investigate the relationship between the mobile game features and their success in terms of the number of downloads and the gross revenue. This paper extends a previous work that analyzed the importance of 37 features of performing a linear regression on 34 games inside Top 100 games from both download and grossing charts. The current research analyses 60 games inside the Top 100 games and also 40 between the Top 400 and Top 500 games. Besides including more games that are more widespread in the chart, we also perform other analysis including data discrimination and classification techniques to compare successful games against unsuccessful ones. A decision tree model is trained to identify frequent patterns and discover useful associations and correlations within data. Besides that, a linear regression model that maps game features and charts performance is trained using a M5 prime classifier. Results show a different result from previous study. There is no correlation between features and game position on top download charts. Besides, it were identified 9 game features that influence the revenue performance of successful mobile games.

Keywords: mobile games, app stores, top charts, game design, game features, data mining.

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1. Introduction

As mobile game distribution costs gets near to zero, the number of available games on the app stores is enormous and continues to grow. In this context, it is increasingly difficult for game developers to build a mobile game that achieves commercial success (top positions on download and gross charts).

Lots of analytics have been used by game industry in order to get a better understanding on how to increase Acquisition, Retention and Monetization (ARM) of users [refs]. However, the literature is so far scarce concerning the analysis of the impact of some common features in the success of mobile games. Most game related analysis try to identify how exactly an aspect of a game relate to the overall game experience; however they do not associate any game aspects with game commercial success. The aspects of games that have been considered for analysis and optimization include:

A. Research projects that study the effect of narrative on games [1][2][3].
B. Studies that examine the relationship between level design parameters of games and player experience [4][5][6].
C. Research studies that investigate the development of game rules in a dynamic and automatic way [7][8].
D. Articles that investigate the aesthetic side of the games and their influence in players' experience [9][10].

This paper is meant to enrich the insufficient literature on the evaluation of features and their impact on mobile game success. This paper extends a previous one that has analyzed the importance of 37 features related to the freemium business model [ref]. In this previous work a linear regression was performed on these features for the top 34 games from both download and grossing charts.

The current research analyses 60 games inside the Top 100 games and also 40 between the Top 400 and Top 500 games. Besides including more games that are more widespread in the chart, this new study makes it possible to create two groups of games – one with good performance and other one with bad performance. This has allowed us to perform not only a linear regression on features and correlate them with game performance, but also perform other analysis including data discrimination and classification techniques.

Our method uses real data from highly successful mobiles games. Firstly we present a list of features related to the freemium business model. These features were used to analyze mobile games on top download and grossing charts of Google Play app store. Their degree of success is measured based on their current position on these charts. A decision tree induction and linear regression analysis were conducted to estimate the relationship between features and their performance. The results found were appreciated and commented by a group of experts in gaming industry.

On previous work, it was identified 6 game features that affect top download charts. However, this research has identified no correlation between features and position on top download charts. Besides, previous research has identified 5 game features that affect top grossing charts and the current research has discovered 9 features. This paper significantly expanded the previous study and presents cohesive and meaningful results to deepening the understanding of mobile game success.

2. Problem

Global game industry revenue reached 93 billion dollars in 2013 and it is growing at a solid rate of 25% per year. This revenue comes from various sources. There are distinct gaming platforms such as consoles, portable consoles, MMOGs, browser, and mobile devices. The latter one however is driving much of the industry growth. Nowadays, there is more than 850,000 and 700.000 apps on Apple App Store [11] and Google Play store [12], respectively. One of the main reasons for the success of this platform is the digital distribution of content. It is secure, fast and cheap. It has also influenced the development of new business models.

The most popular business models in game industry used to be the Premium one. It refers to a product that requires users to pay before using. In spite of that, a new business model arose. The freemium is a business model where a game is provided free of charge, but money is charged for advanced features, functionality or virtual goods. The word "freemium" is a portmanteau neologism combining two aspects of this business model: "free" and "premium".

Nowadays, a total of 69% and 75% of gross revenue from iOS and Android devices comes from freemium games, respectively. Besides that, 98 out of the 100 most profitable games on both platforms - iOS and Android - are freemium games. The mobile game players are willing to spend an average amount of 14 US dollars per transaction (in-app purchase). That is an amount way bigger than the average 0.99-1.99 price tag used on premium games. Among all purchase price points, over 5% of all purchases are for amounts greater than $50, which rivals the amount paid at retail for top console and PC games.

As distribution costs get nearer to zero, it makes sense to give the game away for free because it allows people to discover them. Giving it for free helps a company get scale. With scale, there are more ways to monetize than a single, up-front transaction. The two main monetization ways are described below:

A. Direct monetization: In-App Purchases (IAP)
This revenue stream is associated with direct sales through purchases of virtual goods inside the game. The most successful games that use IAP as their primary revenue source are listed in the top gross (revenue) list of app stores. The best examples nowadays of great revenue using IAP are the games Clash of Clans and Hay Day. They generate more than 2.4 million dollars in a daily basis [13].

B. Indirect monetization: Advertising
This form of monetization entails embedding an advertisement into the game. It is intended to attract traffic to a brand, product or service by linking to the advertiser’s website. The greater is the number of players, the greater is also the number of ads impressions and clicks. Thus, the revenue from advertising is directly proportional to the user base’s size. It is a good estimation to predict that the most successful games that use advertising as a revenue source are listed in the top download list of the app stores. A good example of Advertising revenue is Fruits Ninja of Half Brick. Fruits Ninja generates about 400,000.00 USD per month only in Ads [14].

This change from premium to freemium is recent. In the first semester of 2011, freemium became the dominant business model. It reflected a change in the way people consume and interact with games. Players expect a long-term relationship, and game developers should be ready to provide it. Nonetheless, traditional games that are usually distributed through the premium model do not necessarily work and monetize within the freemium model. Therefore, many game developers are facing problems to adapt their team and process to this new baseline.

This paper brings light to the discussion of how to develop games under current panorama. It provides useful insights for game developers and researchers on how game features influence the performance of a mobile game, in both positive and negative ways.

3. Features

The analysis of a game can involve many different aspects such as aesthetic, gameplay, experience and so on. We are particularly interested in understand which features matter to make a successful mobile game. In order to select the right game features that drive monetization, we have chosen a group of features related to the freemium business model. The ARM funnel (Fig. 1), developed by the research company Kontagent, is commonly used to describe the model. In practical terms, it visualizes mobile gamers passing through a funnel, divided into three stages acquisition, retention and monetization, throughout their lifecycle within the game. With this info in mind we have chosen a group of related features that can be used to indicate how they influence in game performance.

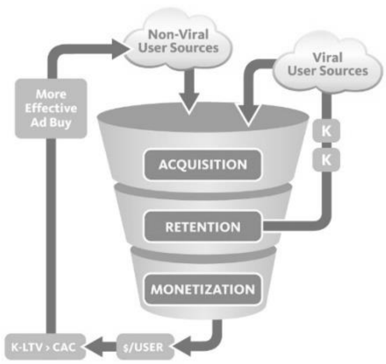

Figure 1: ARM funnel [15].

The acquisition stage deals with how developers can reach out to users, and acquire players. It deals with features that make game social and viral. The retention stage concerns how to keep players around once they have been acquired. Specifically, it deals with features that make game sticky, or addictive, and is closely related to the gaming mechanics and dynamics presented in gamification. The final stage, monetization, looks at the features used in mobile games to generate revenue from their users. The features should provide incentives for players to pay for the virtual goods.

The original features were extracted from the thesis of Peter Askelöf [16] named Monetization of Social Network Games in Japan and the West. They were evaluated and transformed in a more concise list of features. A short description of the chosen features and of the executed changes is described below. For a further description of each feature check the previous study.

ID	NAME	DESCRIPTION
R01	Mobage	A mobile social network very popular on japan
R02	Facebook	The greater social network in the world
R03	Linechat	Another oriental social network
AR01	Request friend help	A Social interaction to keep players in the game and invite new players
A01	Invite friend	Viral acquisition feature
M01	IAP (In App Purchase)	This feature allow users buy virtual goodies in game with real money.
M02	Soft Currency	This is a type of currency that is earned over time much faster
M03	Hard Currency	This type of currency has a linear gain during all game time
M04	Gambling	This game feature is about gambling mechanics on game
M05	Hard Currency Gambling	This feature occurs when the gambling use hard currency[M02]
M06	Soft Currency Gambling	In other hands, this feature occurs when the gambling use soft currency[M03]
RM01	Energy session restriction	In this paper we consider all type of Session limitation as Energy session restriction
M07	Unique offer	It usually represents a great discount and only can bought once by user.
M08	Daily offer	A small discount that help to convert users to paying users.
M09	Event offer	This type of offer is improved by commemorative date like Black Friday and Christmas.
M10	Consumable skip times	It is used to make fast build events or deliver content more quickly.
M11	Timed boost	This feature engages players by a limited time, for example: double coin per one day.
RM02	Power-up upgrade	Upgrades an external element that can somehow improve the score.
RM03	Item upgrade	Also an external status, but this time the item can be affected by other items, thus restarting the evolution.
RM04	Status upgrade	Upgrade the character's base status.
M12	Consumable items	Consumable items differ from upgrades in the sense that they have a non-persistent effect.
M13	Customizable	customizable are usually used on social games to allow players to differentiate themselves from others
R01	Skill trees	The system is very commonly used on RPGs (Role Playing Games)
R02	Content Unlock	The player can unlock contents after game action.
R03	Cumulative reward retention	The player receives an increased reward every day that he comes back to the game
R04	Non-cumulative reward retention	The player always receives the same rewards for coming back to the game regularly
R05	Gambling reward retention	The player receives a random prize by visiting the game on regular time intervals
R06	Punishing absence	Consists of punishing players who don't return to the game with a certain regularity
R07	Single play	This mode is more common on premium games.
R08	Cooperative play	Cooperative games are more common on PC, but there are some games that use this mode on mobile like Clash of Clans or Rage of Bahamut
R09	Competitive play	Usually games with a leaderboard to compete with friends
R10	Versus play	Like cooperative, it’s more common on Console or PC games, but there are games that implement good versus modes like Puzzles and Dragons or Song Pop.
R11	Achievements	Bonus features which are unlocked when players complete certain tasks
R12	Leaderboards	main factor of competitive games, but simply having

		leaderboard doesn't turn a game into a competitive
R13	Levels	According to Askelöf: "Levels are an indication of how far a player has progressed in the game. In games such as Ms. Pac-Man, advancement to the next level was clearly visualized in the game by changing they color of the ghosts and the layout of the maze, etc.".
R14	Random Elements	Gives the player a sense of surprise.
A02	Size	The size that game consume of device hard drive.

4. Methodology

This section describes the experimental method applied to extract, transform, and analyze data. An approach inspired in the CRISP-DM process was used to handle the problem. In the first part of the methodology, it is described how the data was acquired and transformed. After that a decision tree induction and also a regression analysis were conducted to identify the relationship between game features and performance.

An approach inspired in the CRISP-DM process was used to handle the problem. Firstly, we have acquired and transformed real market data from successful games. The top 500 games on both download and grossing charts were investigated. We have identified the presence, or absence, of 37 game features on each of them. Besides that we have evaluated their performance - i.e. position on top charts - for a month. It were collected 30,000 entries related to games' ranking position.

After that a decision tree induction and also a regression analysis were conducted to identify the relationship between game features and performance. The decision tree induction has discovered interesting relationships between variables and developed some rules. The regression method has identified statistically significant correlations.

4.1 Data

This research investigated the top 500 games located inside download and grossing (revenue) charts in the Google Play app store. An analytic total named App Annie was used to extract data from charts for the period between April 11 and May 12 of 2013 [30]. A total of 30.000 entries were collected for further analysis. Each entry consists of a row with four columns: game name, download rank score, grossing rank score and date.

$$Entries = days \times games = 30 \times (500 + 500)$$

Based on previous study, it was identified that the analysis of similar games in terms of performance do not provide enough information to create accurate models. It is necessary to create two distinct groups with successful and unsuccessful games. We have them excluded some entries and considered only games located inside [1,100] and [401,500] position on top charts.

$$Entries = Game \ni \begin{cases} Top\ [1{,}100]\ games \\ Top\ [401{,}500]\ games \end{cases}$$

After the removal of games located between Top]100,400] positions on charts, there were 600 entries to be analyzed. Since games' position change inside the evaluation term, it was necessary to calculate an average position. This value is the final score of each game and is used to define the game performance on both download and grossing charts. The formula for calculating the score is given by:

$$Score(date) = 500 - Min(500, dailyPosition(date))$$

Besides ranking position, that shows the games' implicit degree of success, we have also evaluated the games using an extensive questionnaire. We have played all games in order to fill in the questionnaires. It took around two hours to analyze each game in an objective way. The proposed questionnaire consisted of dichotomous questions and used a closed format. Dichotomous questions force respondents to make a choice, e.g. yes/no questions. Closed format is an objective method, excluding the possibility of expressing opinions about games in a free-flowing manner. The questionnaire contained 37 questions related to different aspects of the game. Its purpose was to identify the presence or absence of features.

After business and data understanding phases, it was started data preparation stage. It covers all activities to construct the final dataset from the initial raw data. Final dataset contains data that will be fed into the modeling tool, e.g. Scores Curves. Activities in this phase include transformation and cleaning of data.

- **Transformation**

The 30,000 entries previously collected were grouped by game. Data acquired from the top charts presents 34 entries for each analyzed game. It refers to the specific position on top charts on each day of research time span. A better position in the charts represents an improved degree of success. A game placed in the Top 100 download charts has a much better acquisition model than a game placed between Top 400-500 games. The same analogy is true for grossing (revenue) charts. In 2012, 15% of all revenue on iTunes was generated by games on top 25 grossing list, and the rest of top 100 generated 17% [17]. It is common, however, to use marketing campaigns to improve overall game performance and insert a new game in top charts. It is a useful and smart approach to improve games' visibility and their chance of being chosen by players. The average ranking position was used in order to reduce marketing effects in game analysis and make viable to focus in the game features that improve the game performance.

- **Normalization**

The main side effect of former data transformation was the identification of high dispersion rates. It indicates that ranking scores are spread out over a large range of values. It was possible to recognize this effect after sorting games using their average ranking position.

It was necessary to normalize acquired data in a [0,1] range, in order to obtain an easier ranking positions' analysis and comparison. After normalization step, games with zero values are ones with the best performance. Then, these ranking values were inverted so that higher score values indicated better game performance. The formula for calculating the normalized value is given by:

$$value = \sum_{date=April\ 11\ of\ 2012}^{May\ 12\ of\ 2013} Score(date) * \frac{1}{30 * 499}$$

4.2 Model

The generation process model involved three steps presented below. In the first step, a Decision Tree Induction was used for the extraction of knowledge about the problem domain. In the following step, a Logistic Regression was responsible for creating a model to identify the most significant variables for the problem.

4.2.1 Decision Tree Induction

A decision tree induction is the learning of decision trees from class-labeled training tuples. The decision tree was built using a top-down recursive divide-and-conquer approach named C4.5 algorithm.

In order to extract knowledge about relationships among predictive attributes and class attribute in the database, a decision tree was generated for each group – grossing and download - based on game features.

In the Figure 2 is presented the Decision Tree model generated after the evaluation of the top grossing games data. The root node (feature = *request friend help*) is responsible for identifying games that contains a social feature to ask for friends help. This feature is considered very important for the evaluation of the game performance in terms of gross revenue. It means that games with this feature has a greater likelihood of have a high revenue.

In addition, the *unique offe*r feature is also of great importance, according to the decision tree. It means that offering good discounts on virtual items that can bought only once by users also improve the likelihood of increase overall game revenue. The decision tree also indicates that games without all these features – *request friend help, unique offer and leaderboard* – has smaller chances to breakthrough in the top gross charts.

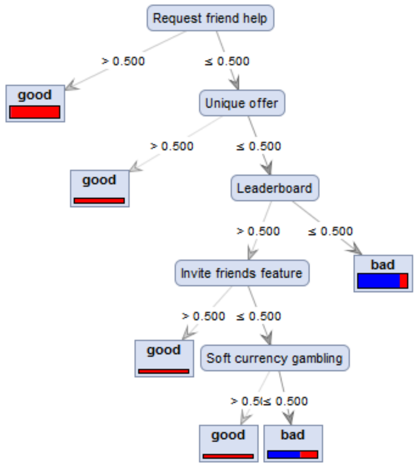

Figure 2: Decision Tree of top grossing games.

It was not possible to generate the Decision Tree model using the top downloaded games data. A root-node only tree was generated culminating in the creation of a null-model.

4.2.2 Linear Regression

A linear regression model was built to extract knowledge about relationships among predictive attributes and the class attribute in database. In statistics, linear regression is an approach to modeling the relationship between a scalar dependent variable (e.g. performance of a game) and one or more explanatory variables (e.g. game features). Linear regression calculates regression coefficients that indicates the effect of each explanatory variable over output model. Thus, it makes possible to identify most representatives' variables in the analyzed problem

Data was divided randomly into two groups: training and test groups. Former one is used to produce the model and contains 70% of the records. The later one is used to test the accuracy of the model and contains 30% of the records. During the use of training set to produce the logistic model, the parameters' estimates associated with the variables of the input set are generated. These parameters, also called regression coefficients, are normalized between [-1, +1] and reflect the effect of a given variable on the output model.

The linear regression model, as a statistical technique to perform estimation, it produces test statistics which can be interpreted using p-values. The p-value indicates the probability that the coefficient for this attribute is equal to zero (thus proving the null hypothesis). In other words, small p-values correspond to strong evidence. If the p-value is below a predefined limit which is often 0.05, the results are designated as "statistically significant".

The results of linear regression is presented on tables I and II and Fig. 3 and 4. They show the list of variables and their parameters. The attributes in table have been sorted by p-value with lower values indicating greater significance for this variable. Besides that, we have omitted the non-statistically significant results for the sake of clarity. The coefficient values represent how each variable influence the performance of a game in both download and grossing charts.

The coefficient absolute value, or modulus, refers to the intensity of the influence on performance outcomes. A greater value means that the feature presents a higher leverage. Furthermore, the coefficient value sign - e.g. positive or negative - is related to how each feature influence on game performance. A positive value means that the analyzed feature influence the overall game performance in a positive way. The opposite is also true. A negative value means that the investigated feature affects the game performance in a negative way.

Table 1: Grossing Results

Attribute	*Coefficient*	*Std. Error*	*t-Stat*	*p-Value*
(intercept)	0,131	0,105	1,255	0,291
IAP Potential	-0,345	0,093	-3,710	0,000
Hard Currency	-0,295	0,096	-3,063	0,003
Time Skips	0,324	0,109	2,964	0,005
Hard Currency Gambling	0,482	0,163	2,952	0,005
Soft Currency	0,272	0,100	2,726	0,009
Leaderboard	0,195	0,078	2,496	0,017
Request Friend Help	0,274	0,115	2,387	0,022
Consumable	0,172	0,075	2,310	0,027
Facebook	0,177	0,083	2,118	0,044
Levels	0,159	0,076	2,074	0,049

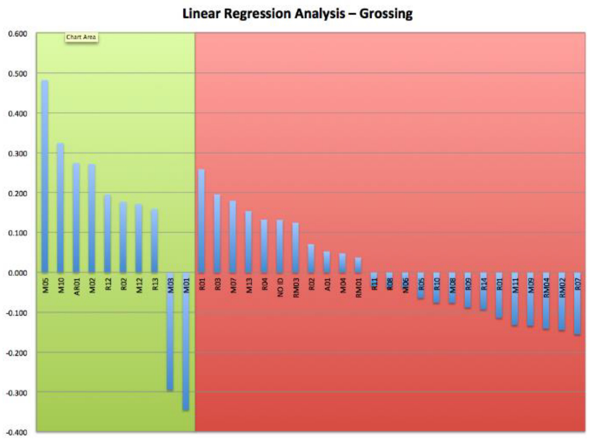

Figure 3: Histogram of top grossing games using coefficient.

Table 2: Download results

Attribute	*Coefficient*	*Std. Error*	*t-Stat*	*p-Value*
(Intercept)	0,471	0,242	1,946	0,066
Hard Currency	-0,486	0,136	-3,566	0,001
Timed Boost	0,464	0,174	2,662	0,011
Soft Currency	0,317	0,137	2,310	0,027
IAP Potential	-0,326	0,144	-2,274	0,030
Leaderboard	0,236	0,107	2,212	0,035
Gambling	-0,320	0,151	-2,115	0,044

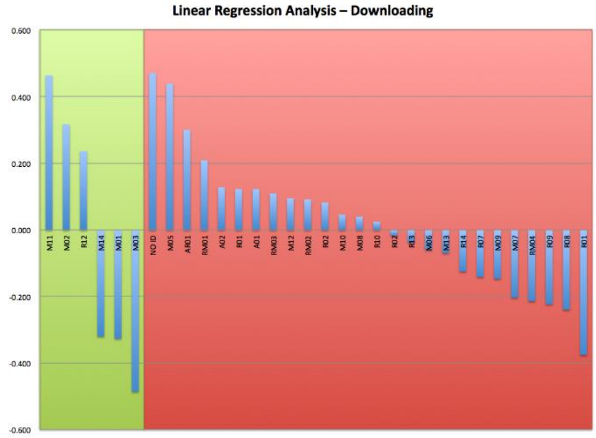

Figure 4: Histogram of top download games using coefficient.

The tables present also an intercept attribute. It is a constant representing the intercept of the line with the vertical axis. In other words, it indicates that even when all of the attributes are zero, there will be some amount of positive influence. It makes sense since all analyzed games are located inside top 500 charts and have an overall good performance.

5. Performance Evaluation

In order to evaluate the performance of the classifications, the following metric was applied to both models: Decision Tree and Linear regression.

5.1 ROC Curve

The statistical test named Receiver Operating Characteristic curve (or ROC Curve) is a graphical plot which illustrates the performance of a binary classifier system. The accuracy of this method depends on how well the test separates the group being tested into those with and without a good performance on the top charts. Accuracy is measured by the area under the ROC curve. An area of 1.0 represents a perfect test; an area of 0.5 represents a worthless test.

In the Figure 5 is presented the Roc Curve of the Decision Tree. The area under this curve is 0.78. This model also contains an accuracy of 79.00% and a precision of 86.86%. In summary, both models created for classifying top grossing games present a good performance on identify and classify games based on their features.

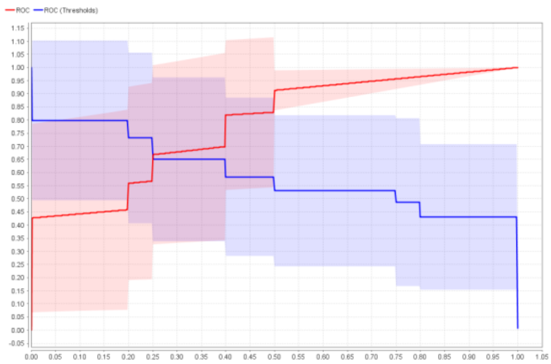

Figure 5: ROC Curve of the Decision Tree model for top grossing games.

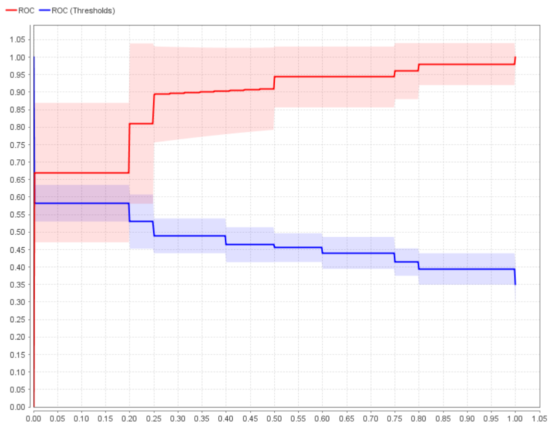

Figure 6: ROC Curve of the Linear Regression model for top grossing games.

On the other side, the models generated using top downloaded games data have not showed a good performance. The decision tree generated contains only the root node. This type of decision tree is considered a null model with a performance similar to a random one. This information is confirmed by its area under the ROC Curve that it is 0.50. The Linear Regression generated has also presented a bad performance. The area under its ROC Curve is 0.694. Besides that, it has an accuracy of 59.00% and a precision of 62.14%.

6. Analysis

This section discusses the main findings of the approach used to analyze which features have influence in the performance of mobile games. The information acquired from the models, including statistically significant correlations, were evaluated by a group of specialists to elucidate and justify all results found. Producers and designers with more than 10 years of experience in game development form the team of experts. Initially, the models created for the download ranks are analyzed and then all features associated with games in the top grossing charts are evaluated.

6.1 Download

The models generated to evaluate which features influence the performance of games in the top downloads charts presented a bad performance. It was not possible to discover the most statistically significant features. There are some possible reasons for that such as the following ones:

- The amount of data acquired is not enough to model the problem.
- The modelling techniques used are not suitable for this genre of problem.

However, the team of experts strongly believe that the real reason is that the top download charts are affected by external marketing campaigns. It is possible to perceive this phenomenon by analyzing the early outcomes related to simple statistical data.

Average and standard deviation values present useful insights to understand this behavior. The Table IV shows that both mean and standard deviation are higher on download charts compared to grossing ones. There is a higher mobility on these charts and it means the list of games on download ranks changes more quickly.

Table 3: Statistical information.

Type	*Average*	*Standard Deviation*
Top Download (1-100)	28.066	33.263
Top Download (400-500)	430.426	58.141
Top Grossing (1-100)	9,617	17,527
Top Grossing (400-500)	464.171	27.909

This unique characteristic of the top download games creates a random effect on charts. There are no patterns to be analyzed because mobile games achieve a better position on charts based on the size of their marketing budgets. This hypothesis explains why there is no correlation between game features and games' position on top downloads charts.

6.2 Grossing

All models created using data from top grossing games were statistically significant. After excluding features with low relationship discovered by p-value, we had 10 features that affect grossing rank. The table IV shows these features and the type of effect of them. A positive sign means that the feature is related to a better game performance. On the other hand, a negative signal means exactly the opposite.

Table 4: Top grossing (revenue) game results.

Download		*Grossing*	
⊕	⊖	⊕	⊖

Timed Boost Soft Currency Leaderboard	Hard Currency IAP Potential Gambling	Time Skips Hard Currency Gambling Soft Currency Leaderboard Request Friend Help Consumable Facebook Levels	IAP Potential Hard Currency

With the help of game specialists, we discuss each of identified representative features that affect games performance. In order to fully understand all explanations it is important to be aware of some concepts and terms.

We can admit Average Receipt Per User (ARPU) is a function of receipt by number of users (1) and we can also admit that average receipt per user is a function of Conversion Rate (CR) and Average Receipt Per Paying User (ARPPU) (2). Then to constant downloads number, we have two aspects that affects receipt (3): ARPPU and CR [18].

$$ARPU = \frac{Receipt}{Downloads} \quad (1)$$

$$ARPU = ARPPU * CR \quad (2)$$

$$Receipt = ARPPU * CR * Downloads \quad (3)$$

- **Time Skip (+0.306)**

A traditional approach for game progression is speed up player evolution in the beginning of the gameplay. It makes players get used to a fast pace. After a while, the game slow it down deliberately and game actions that used to take a few minutes will start to take days to complete. In this scenario, players are compelled to buy Time Skippers to keep game progression fast and do not wait too long for actions to be completed. It helps games to increase their conversion rates. According Katkoff: "Players are primed to spend when their progression slows down over time and they are constantly comparing their progress through social interaction inside the game" [20].

- **Hard Currency Gambling (+0.282)**

The gambling industry revenue is even bigger than the game industry one. Unsurprisingly there are many casino games inside the Top 100 grossing charts. This type of game has a unique structure and mechanic to drive users to spend money. Even traditional games – not casino ones – use some of the usual gambling game mechanics to make users spend hard currency. These games include some casino-like mini-games such as slot machine where users can try to win virtual itens by spending hard currency. Since hard currency can only by acquired by spending real money, this feature helps games to increase their revenue and gets a better position on top grossing (revenue) charts.

- **Soft Currency (+0.285)**

This type of currency is earned by completing specific tasks inside the game. It means that players do not need to spend money to acquire them. The soft currency is usually spent to buy virtual items – especially consumables ones. Although the game developers do not earn anything from purchases made with soft currency, it makes players get used to visit in-game store, look for virtual items and buy them. This type of feature makes players more willing to spend money and this is the main reasons this feature helps games to increase their revenue.

- **Leaderboard (+0.230)**

Leaderboards is a fun way to drive competition among players, both for hardcore and casual players. The former will be fighting for the top spot in a public leaderboard while the later will be interested in comparing their progress to their friends'. This is an important feature to increase replay-value without adding more content to the game. It improves a lot the entertainment value of playing a game more than once. Since game revenue is intricately related to players' retention, it is expected that this feature would help games to increase their revenue.

- **Request Friend Help (+0.249)**

A common approach for successful games with social features is lock game progress until players' execute one of the following actions: wait for a fixed time, request friend help or spend money to unlock. Most games makes players get used to a fast pace, thereby they are usually not willing to wait. Players then try to ask for friends help to unlock game progression. This action also takes a while to be completed and players could not get friends help too. The third option is the fastest way to unlock content and continue playing. It also have a plus. After players try to ask for friends help and do not get succeed on that they are willing to pay with no worries. They will not think that they are using an evil strategy called pay-to-win because this entire mechanism hides this fact.

- **Facebook (+0.194)**

The social networks such as facebook help users to find games, challenge friends and ask for help. These social features keep users engaged and increase the viral aspect of the game. It means that when players like or share game-related content it helps other users to find the game. More players means more users willing to pay for virtual items, upgrades and premium content. Since facebook has the biggest user base, it helps a lot game developers to acquire more users and increaser their revenues.

- **Levels (+0.169)**

The presence of a level system usually give players a feeling of game progression. This feeling make users want to play more in order to discover new features and challenges. It helps a lot to increase user retention. It is important to retain users for as long as possible to have more opportunities to make them buy virtual itens and spend money inside the game. It means more chance to convert a free user in a paying user increase overall game monetization.

- **IAP Potential (-0.394)**

At first glance, it is not expected that IAP Potential would have a negative correlation with game revenue. However it is important to remember that this feature only includes purchases made with real money of non-consumable items. In other words, it only includes purchases like pack of levels and remove ad banners. It does not include soft and hard currency consumption and consumable goods such as lives and power-ups. Since freemium gamers spend most of their games on items they don't keep – aka consumable goods – the bad performance of this variable makes complete sense.

7. Conclusions and Future Work

This paper presented an evolution of a previous research related to the evaluation of which features matters to build a successful game. We acquired more data to expand the results of the previous work by including data from games with poor performance. With this extra information, it was possible to apply more data mining techniques to better understand the relationship between features and performance. It became also possible to develop a binary classification model.

The analysis of the data demonstrated a relationship between some features and the performance of games on grossing (revenue) charts on Google Play. A linear regression approach has exposed the degree of relationship and also the confidence interval of each game feature. There are two main findings on how features affect performance on the Google Play store.

In terms of gross revenue performance, the following features has a positive correlation with on grossing charts: hard currency gambling, time skips, request friend help, soft currency, leaderboard, facebook, consumable and levels. On the other hand, only two features have a statistically significant correlation with negative performance of games on grossing charts: hard currency and IAP Potential.

In terms of download performance, it was not possible to identify any statistically significant relationship between performance and features. The main hypothesis for achieving this result is due to the massive budgets spent on games' release. It creates a random flow of multiple games on top download charts with no relationship between them.

The research findings provide important clues about which features really matter to create a successful mobile game. It indicates the direction that developers should follow to build mobile games to monetize in a better way and achieve top positions on gross charts.

In our future work, we will acquire more data to expand the results of the presented work. It is demanding to extract data from even more games and from other platforms such as iOS and Amazon. With this information, it will be possible to not only evaluate the similarities and differences between the main mobile app stores, but also develop a binary classification model. In this case, the classification model could be used to identify the successful chance for a given game on each mobile app store. This approach can also be used to suggest a feature for a game based on the associated increase in their performance probability.

References

[1] Roberts, David L. "Computational techniques for reasoning about and shaping player experiences in interactive narratives", Georgia Institute of Technology, April 6, 2010.

[2] H. Jenkins. "Game Design as Narrative Architecture", anabiosispress.org. [Online]. Available: http://www.anabiosispress.org/VM606/1stPerson_hjenkins.pdf [Accessed: July 12, 2013].

[3] R. Michael Young and Mark Riedl. "Towards an architecture for intelligent control of narrative in interactive virtual worlds." In Proceedings of the 8th international conference on Intelligent user interfaces (IUI '03). 2003.

[4] Chris Pedersen, Julian Togelius and Georgios N. Yannakakis. "Modeling Player Experience in Super Mario Bros". 2009.

[5] Gillian Smith, Mike Treanor, Jim Whitehead, Michael Mateas. "Rhythm-Based Level Generation for 2D Platformers". 2009.

[6] Peter Mawhorter, Michael Mateas. "Procedural Level Generation Using Occupancy-Regulated Extension".

[7] J. Togelius, Lugano IDSIA, J. Schmidhuber. "An experiment in automatic game design". 2008.

[8] Mark J. Nelson, Michael Mateas. "Towards Automatic Game Design". 10th Congress of the Italian Association for Artificial Intelligence, Rome, Italy, pp. 626-637, October 2007.

[9] D. Myers. "A Q-Study of Game Player Aesthetics". Simulation & Gaming, pp. 375-396, December 1990.

[10] Thomas W. Malone. "Heuristics for designing enjoyable user interfaces: Lessons from computer games.". In Proceedings of the 1982 Conference on Human Factors in Computing Systems (CHI '82). ACM, New York, NY, USA, 63-68. 1982.

[11] M. Rodrigues. "App Store da Apple atinge marco histórico de 50 bilhões de downloads", Apple.com, May 16, 2013. [Online]. Available: http://www.apple.com/br/pr/library/2013/05/16Apples-App-Store-Marks-Historic-50-Billionth-Download.html [Accessed: July 12, 2013].

[12] B. Womack. "Google Says 700,000 Applications Available for Android", businessweek.com, October 29, 2012. [Online]. Available: http://www.businessweek.com/news/2012-10-29/google-says-700-000-applications-available-for-android-devices [Accessed: July 12, 2013].

[13] K. Strauss. "The $2.4 Million-Per-Day Company: Supercell", forbes.com, April 18, 2013. [Online]. Available: http://www.forbes.com/sites/karstenstrauss/2013/04/18/the-2-4-million-per-day-company-supercell/ [Accessed: July 12, 2013].

[14] J. D. Rey. "Mobile App Economics: 'Fruit Ninja' Makes $400,000 a Month on Ads", Adage.com, July 11, 2013. [Online]. Available: http://adage.com/article/digital/mobile-app-economics-fruit-ninja-makes-400-000-a-month-ads/235965/ [Accessed: July 12, 2013].

[15] Kontagent, "The top 7 metrics of high Successful Social Companies", kontagent.com. [Online]. Available: http://static.kontagent.com/whitepaper/KNT_WP_Top7Metrics_P3_finalx.pdf [Accessed: July 12, 2013].

[16] P. Askelöf, "Monetization of Social Network Games in Japan and the West", Lund University, Faculty of Engineering, LTH, 2013.

[17] M. E. Gordon, "The History of App Pricing, And Why Most Apps Are Free", flurry.com, July 18, 2013. [Online]. Available: http://blog.flurry.com/?Tag=App%20Revenue [Accessed: July 12, 2013].

[18] M. Katkoff, "From Players to Payers", deconstructoroffun.blogspot.com, May 4, 2012. [Online]. Available: http://deconstructoroffun.blogspot.com.br/2012/05/from-players-to-payers-4-steps-to.html [Accessed: July 12, 2013].

[19] NAME_REMOVED.

[20] M. Katkoff, Mid-Core Success Part 4: Monetization. Available: http://blog.gameanalytics.com/blog/mid-core-success-part-4-monetization.html

[21] G. Zichermann and C. Cunningham, Gamification by Design: Implementing Game Mechanics in Web and Mobile Apps, O'Reilly, 2011

[22] M. Katkoff, Mid-Core Success Part 3: Social. Available: http://blog.gameanalytics.com/blog/mid-core-success-part-3-social.html