A Produção do Conhecimento na Engenharia da Computação

Ernane Rosa Martins
(Organizador)

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APRESENTAÇÃO

Segundo o dicionário Aurélio a Engenharia é a “Arte de aplicar conhecimentos científicos e empíricos e certas habilitações específicas à criação de estruturas, dispositivos e processos que se utilizam para converter recursos naturais em formas adequadas ao atendimento das necessidades humanas. A Engenharia de Computação é definida como o ramo da engenharia que se caracteriza pelo projeto, desenvolvimento e implementação de sistemas, equipamentos e dispositivos computacionais segundo uma visão integrada de hardware e software, apoiando-se em uma sólida base matemática e conhecimentos de fenômenos físicos.

Este livro, possibilita conhecer algumas das produções do conhecimento no ramo da Engenharia da Computação, que abordam assuntos extremamente importantes, tais como: as transformações sofridas nos processos de projeto desde a implementação das ferramentas digitais; o armazenamento, indexação e recuperação de formulários digitais; a reabilitação motora assistida por computadores; a reflexão acerca do realismo e da representação visual em jogos digitais; os padrões de players em ambientes virtuais; as soluções tecnológicas relevantes usadas em países africanos; a complexa relação existente entre jogos digitais e o humano; a dinâmica da comunicação de um grupo de Facebook criado em um processo de urbanismo bottom-up; o estado da arte das pesquisas e estudos acadêmicos acerca dos elementos visuais contidos na interface de jogos digitais; as estratégias de design que integrem tecnologia computacional digital a artefatos e instalações para a interação de visitantes em museus; os jogos que abordam o tema de mitologia e religião.

Deste modo, espero que este livro seja um guia para os Engenheiros de Computação auxiliando-os em assuntos relevantes da área, fornecendo conhecimentos que podem permitir especificar, conceber, desenvolver, implementar, adaptar, produzir, industrializar, instalar e manter sistemas computacionais, bem como perfazer a integração de recursos físicos e lógicos necessários para o atendimento das necessidades informacionais, computacionais e da automação de organizações em geral. Por fim, agradeço a todos que contribuíram de alguma forma para a construção desta obra e desejo a todos os leitores, novas e significativas reflexões sobre os temas abordados.

Ernane Rosa Martins

SUMÁRIO

CAPÍTULO 5

PLAYER GAME DATA MINING FOR PLAYER CLASSIFICATION

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ABSTRACT: Analyzing and understanding the standard of players in virtual environments has been an activity increasingly used by digital game developers and producers. Players are the main reason that games are developed and knowing the main characteristics for each of your player is fundamental for game developers have a successful product. In the case of Massively Multiplayer Online Role Playing Games ("MMORPG"), the types of players vary, and, by classifying players' behaviors, it is possible for developers to implement changes which satisfy players in targeted manners which may impact their level of interest and amount of time spent in the game environment. This study suggests that it is possible to identify and classify players via gameplay analysis by using consolidated theories such as Bartle's archetypes or Marczewski's types of players, which group players with the k-means algorithm. Below, is presented a dedicated section describing the Game Analytics processes and a session with the results obtained from the analysis of a specific guild from World of Warcraft.

KEYWORDS: game analytics, taxonomy of Bartle, classification of players, MMORPG, k-means

1 I INTRODUCTION

According to [1] there are 2.2 billion players around the world today who created $108.9 billion dollars in videogame revenue in 2017, split by mobile devices (42%), PCs (27%) and consoles (31%).

It can be deduced that the digital game market is enticing to investors, since gaming companies started to use new technologies to customize player experiences and incentivize customer loyalty to their products. One of these technologies is game data mining, which searches players' information through gameplay telemetry [4].

Analysis of telemetry data can be executed by utilizing game data mining tools and the results can be used to classify players who play certain games, their behaviors in the game, and their gameplay patterns. Having possession of this information allows producers to initiate new developments of games, expansions to the current game, and marketing actions to attract new players, among other possibilities.

For producers, it is important to try to profile players based on their style or way of playing and, since Richard Bartle's research on the types of players who play Multi User Dungeon ("MUD") [3], the research area of player's classification has gained widespread recognition and has been applied in different areas, from identification of MUD players such as Game Design and gamification [4, 5, 7, 8, 9]. While other researchers have attempted to develop more robust taxonomies that involve more types of players as in [7], the area that was originally created by Bartle, there is only one questionnaire developed [6] that classifies the type of player in a MUD or MMORPG based on Bartle's type of players.

According to [5], Bartle's theory needs improvement since the types of players are not correlated and may be overlapping. [5] argues that the model cannot be empirically validated. An example of the application and empirical validation of the types of gamers can be found in [4], where an analysis was created through game analytics and game data mining to identify the types of players who play a specific game, but there are no academic articles (Elsevier, IEEE Explorer and Web of Science in the period 2009 to date) on the validity of Bartle's taxonomy and its applicability to MMORPG games.

This work aims to identify the possible data that can be used to classify the players as one of the four types of players of the archetype of Bartle in a certain database of the game World of Warcraft.

2 | DATA TELEMETRY AND GAME DATA MINING

Data is created from the moment one initiates a virtual game session until the moment it is turned off, and this data is available for developers and producers to analyze their players. Data created and collected by the developers are known as game telemetry

Telemetry is a remote form of data collection where a game-player interaction data collection application is installed in the desired game and sends data digitally to a database that stores all information in an accessible way so that an analysis of said data may be performed. These data can be of any nature that the game allows and may contain information on the player's behavior within the game, transactions made, and conversations amongst multiple characters [2].

Developers use this data to form statistical models to have a better understanding of their players and games. The difficulties that are encountered are: (1) knowing what data will be analyzed and utilized to find the desired models; and (2) where the data will be stored because it is a very large volume of data, and processing delays can occur when trying to analyze in a conventional manner. [7], [8].

To perform the data analysis task, one may use game analytics tools. The definition of analytics in [2] is a process of discovering and communicating patterns in data to solve business problems or to make predictions to sustain managerial decisions, perform actions and / or improve performance. The methodological foundation of analytics is statistical, data mining, mathematics, programming and operational research.

An offshoot of analytics is game analytics, which is the application of analytics tools in game development and research.

When it comes to making game-related decisions, using game analytics can bring insights varying from game design aspects to marketing actions, and it is typically performed with one ultimate goal: to give a better experience to the end user [2].

The data that has been selected and stored in the databases is called game metrics, and these metrics allow one to analyze the behavior of players in certain games. This analysis is called game data mining [9].

Some treat data mining as knowledge discovery from data ("KDD"). The difference between KDD and data mining is that KDD is seen as a general process for extracting knowledge from the data, while the latter is the application of specific algorithms for the extraction of desired information from that data without the application of any other KDD process [10].

According to [10], data mining is a process that seeks to discover patterns and knowledge in a large amount of data. The term in question refers to the old techniques of gold mining, since a considerable amount of ore had to be mined in order to obtain a small gold gem.

Game data mining is a version of data mining for digital games. Data mining is a tool that has become increasingly used in social networking, gaming, banking, military intelligence, satellites, the internet and in any other environment that generates large volumes of data to be analyzed [5].

2.1 Data clustering and k-means

One technique to analyse game telemetry data is data clustering, which is the process of grouping data into small clusters. Each cluster groups similar data which are distinct from one other. [10], [11].

Clustering is a method that uses unsupervised neural networks, networks that have no need to know the desired output, learning with input data only [12],[13].

For this experiment, k-means clustering method was used because there are other studies using this method to classify and group types of players [7], and even outside of gaming literature this method has been used to cluster data [17]. K-means is an algorithm where the number of clusters (k) are chosen and each cluster centroid is initialized in a distinct place of the dataset. After the initialization, centroids are iterated and, based on the Euclidian distance between data and the cluster's mean, centroids move and start grouping the data into clusters until there are no movements needed and the clusters are set [10],[11]. This can be seen in Figure 1.

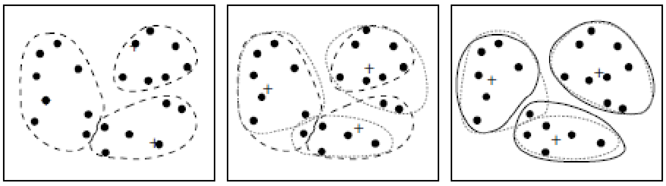

Figure 1: Data clustering using k-means from the initial clustering (a), iterate (b) and final clustering (c) [10]

Although k-mean is an effective method, it still has room for improvements, such as the means of selecting the number of clusters. For this experiment, the number of clusters was set to 4 since it is the total of Bartle’s types of players. All datasets must have a numerical sample because the algorithm depends on the distance means between each point to be calculated.

The next section will explain Bartle’s types of players.

3 I BARTLE TAXONOMY

Richard Bartle [3] developed a taxonomy for categorizing MUD (Multi User Dungeon) players. The result was four types of players: Killers, Explorers, Achievers, and Socializer.

With these four types of players can be discovered the player profile and this is used by the game developers to implement improvements to extend the game lifecycle. These four types can be seen in Figure 2.

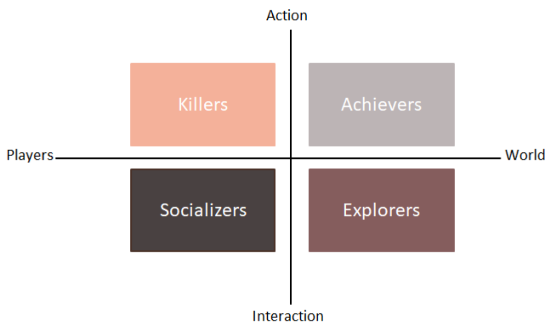

Figure 2: The four types of players and their performances in the game world [3]

The horizontal axis starts with the Players on the left and ends in the Environment (Game World) on the right, while the vertical axis begins with the Interaction on the bottom and ends with the Action on the top. Players are arranged in each of the quadrants per the definition of the types of players above [3].

Achievers are players who play based on collecting as many items as possible within a game, whether they be higher scoring, rare objects or even small game rewards. The characteristic of these players is to try to find some advantage when participating in group missions, to count the amount of experience that is needed to move up a level, or the amount of points to reach the maximum score. Achievers like to act on the game environment in which they find themselves [3].

Explorers play with the motivation to exploit the game as much as possible, but not only in the direction of the game map but also every detail, every fault, every opening in the game so that one can take advantage of the environment. An explorer feels fulfilled when he finds something that no one has ever encountered, whether it is a hidden route or a combination of never-tried moves that activate a special power of a character. Explorers like to interact with the game environment in which they find themselves [3].

The motivation of Socializers is to be able to interact with other players, and as a good RPG (Role Playing Game), represent characters in the best possible way in the virtual environment to allow such interactions. The game itself, for these players, is not their main motivation, instead to be able to interact with the friends made alongside the gameplay, to be able to share experiences outside the game, and even to hold meetings so that everyone can play together in the same environment. Socializers tend to have an intense interaction among them [3].

Killers are the players who like to impose themselves on people in the virtual environment. There are players who feel accomplished by killing other people's characters, or when they provoke other players during the game session. Killers are players who act on players who are in the same environment as themselves [3].

MUDs can be considered one of the first Massive Multiplayer Online ("MMO") games where players come together to play in a virtual environment and there is a study developed by Andreasen and Downey which classifies the players through a quiz. The verification of archetypes has already been done through game analytics [4], and it is hoped that with the use of game analytics it will be possible to identify the type of players from Bartle's taxonomy.

4 I WORLD OF WARCRAFT AVATAR HISTORY DATASET

The game World of Warcraft (WoW) was used for this experiment because it fits the definitions of a MUD: Online multiplayer game set in a virtual world that is played in real time [14]. Although it no longer has the popularity of its early years, WoW is still a game with many active players: 5.5 million players at the end of the third quarter of 2015 according to the last official publication of Blizzard (official game producer and distributor) [14].

The dataset chosen was the World of Warcraft Avatar History (WoWAH), which was extracted from the game over a period of 3 years (January 2006 to January 2009) providing data from a total of 91,605 avatars [15].

Although it is a relatively old database, it is a database still used in some research ([8], [15]) as well as hackathon exercises [16].

The following data from WoWAH were collected and stored during the three years of the observation period: data capture date and time, data collection sequence, Avatar ID, Guild, Level, Race, Class and Game Zone in which the player is. This data was collected from Taiwan's Light's Hope server. The game still possesses two factions: Alliance and Horde, the data were extracted from the Horde faction [15].

For this study, a reduced data set was selected because it was a first test with the data. The data is from the year 2008 and represents the data of all its users that year [16].

In order to start the experiment, there needed to be some adjustments to the data, including adding additional columns as shown in tables 1 and 2.

Title	Characteristics
Char	Int > 0
Level	Int > 0
Race	Available Races in game
Charclass	Available Class in game
Zone	One of the 229 zones in WoW
Guild	Int > 0

Table 1: initial data available in reduced wowah extraction

Title	Characteristics
Char	Int > 0
Level	Int > 0
Race	Available Races in game
Charclass	Available Class in game
Zone	One of the 229 zones in WoW
Guild	Int > 0
Timestamp	Jan,2008 to Jan,2009
Current Date	Date
Hour	Int from 0 to 23
Month Index	Int from 1 to 12
Activation Date	Player activation date – from Jan 2008 to Jan 2009
DSI	Days Since int 0 or 1
Type	Grouping of Class and Races

Table 2: Wowah data set for experiment

5 I RESULTS FROM THE ANALYSIS

The objective of the experiment was to observe if it was possible to identify Bartle's 4 types of players in a MMORPG environment. For that it was needed to understand how the players behave in this environment and the regions that players play.

An account was created and, for three months, players were observed in the five regions available in the WoWAH: Capitals, Battlegrounds, Outlands, Northrend and Arena. Each region has its particularities that attracts more certain types of players and are described below.

Capitals are the base for each race where players can upgrade their characters, also has banks, auction houses, stores. And for being a combat-free zone, players spent most of their time in these cities interacting with other players or Non-Playable Characters.

Battlegrounds is a group PvP region, where players must compete against other teams. Players can build their team and play with strategies to win the battle. Each win gives the team points that can be exchanged for items later.

Outland and Northrend was, in 2008, the only regions wher players could look for missions and level up. Also, in these regions players could explore and look for rare items, or new paths for their adventures.

Arena is the pure PvP region, where players can join the area and fight against other players without the need of grouping.

In each region was possible to identify similarity with each of the Bartle's type of player. Besides it doesn't fulfil 100% each player type, each region tends to bring more one type than others. For this study it was associated as follow: Arena and Capitals are regions that pleases Socializers, Battlegrounds for Killers, Northrend and Outland for Explorers and Achievers.

Based on these assumptions, were chosen also the total hours played by each player and how many times each player visits each region. The data was grouped by the k-means algorithm were the number "k" was defined as the number of Bartle's type of player: 4. Results can be found in figures 3 and 4.

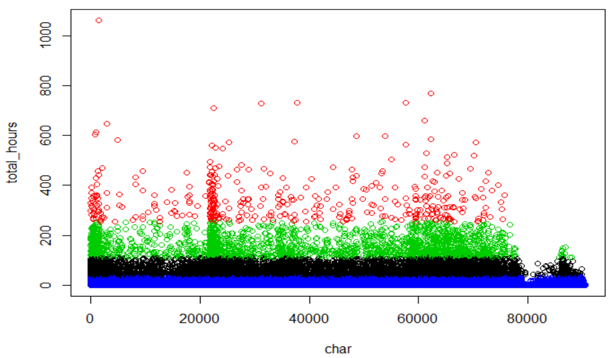

Figure 3: Total hours played by each player and its clusters

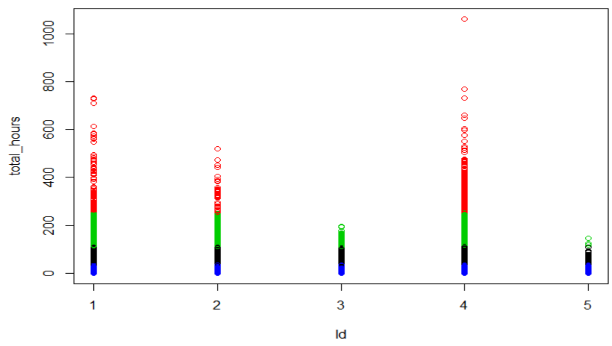

Figure 4: Players grouped by amount of hours played in each region

When it's analyzed the number of hours spent in each region, can be noticed that regions 1 and 4 are the ones where players spend more hours on. Region 1 are Capitals; 2 Battlegrounds; 3 Northrend; 4 Outland; and 5 Arena. Concluding that it's possible identify players with tendencies for Killers (region 5), Socializers (regions 1 and 2) due the regions tends to attract players with that characteristic.

In order to identify Explorers and Achievers it was done another grouping only on regions Northrend and Outland with the amount of times each player returned to these regions and amount of hours spent. Results are presented on figure 5.

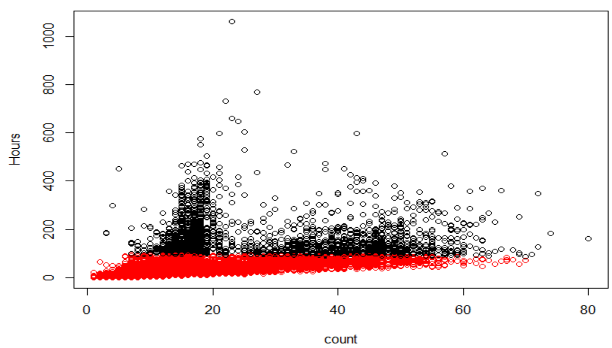

Figure 5: Number of times each player visited Outland and Northrend regions and amount of hours spent

It was used k-means algorithm, with k=2, to verify the possibility to identify Achievers and Explorers characteristics in the dataset. Players are split in two groups and it's possible to verify that red group plays more hours (150 plus hours) and return less to the regions, which can match the behaviour of an Explorer. While the black group plays up to 150 hours and return more often in the regions. Achievers only interacts in a region to fulfil their objectives, once it's done they move to other places.

The number of players distributed per type of player can be found on table III.

Socializer	Killer	Achiever	Explorer
35587	2785	1921	13954
66%	5%	4%	26%

Table 3: Distribution of player per cluster

What can be concluded with the results is that players, most of the time, behaves as Socializers, then Explorers, while Killers and Achievers comes right after those types.

One of the reasons this could happen would be due 2008 was not a good year in terms of major game updates, the major update was done in November of 2008 with Warth of the Lich King being launched 22 months after a major release. This means that for 22 months players didn't have new maximum character level, or different dungeons or areas to explore, what they could do was meet with friends and play altogether.

6 I CONCLUSION AND FUTURE WORK

In this experiment it was possible to verify player composition and define how these players spent their hours playing the game.

It can be noted that players spent most of their hours playing in regions identified for Socializers regions, then in Explorers region, and lastly in Killers and Achievers region.

It can't be more precise due the lack of information from the data set on the Socializers like number of friends or messages exchanged in game with friends.

Based on this information, game developers can identify the players game play characteristics and perform some direct marketing, apply changes to game mechanics, create new missions for a specific player type, and develop new regions or missions that can bring newer or older players, among other actions that can satisfy each type of player.

For future work, can be analyzed the movements between regions and the time to level up to better identify Achievers and Explorers and propose an improved method to identify these types of players, not only based on hours.

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