

Data Streaming and Real-time Analytics unit 3

Case study: Game Analytics

paper: A game analytics model to identify player profiles in singleplayer games

Outline

- Game Industry
- Game analytics
- Bartle's Taxonomy

Game Industry

- A highly competitive industry
- Game designers need better strategies to create an attractive gameplay, high replay value (keep players coming back multiple times)
- Well-known strategy is to use game data to analyse player behavior, focusing on improving specific gameplay characteristics
 - **Game Analytics**

Game Analytics

- The science of online analysis and metrics of games
- Focusing on the use of player behavior data to increase revenue and avoid users leaving the game too early.
- Behavior analysis
 - Most of the works on player behavior analysis use **Robert Bartle's Taxonomy**
 - 1) Achievers, 2) Killers, 3) Socializers, 4) Explorers

Bartle's Taxonomy

1. Achievers

- focused on mastering the game, on the rewards it has to offer. They share the world with other players, or non-playable characters (NPCs), and add a competitive element to the environment. Therefore, they are proud of their status in the game hierarchy, and how fast they reached their current level.

2. Killers

- focused on acting on other players, or NPCs, most of the time showing their superiority over them. They seek more power and abilities, that can help them affect others. Therefore, they are proud of their level of authority and their fighting skills.

Bartle's Taxonomy

3. Socializers

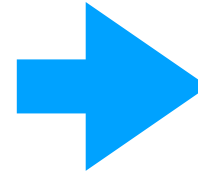
- focused on interacting and talking with other players, or NPCs. Also, finding more about other people is more interesting for socializers than competing, or bossing them. Therefore, they are proud of the relationships and of their influence towards other players.

4. Explorers

- focused on interacting with the world, the game environment. The sense of discovery or finding new areas and game elements fulfills them more than just achieving a great status in the game. Therefore, they are proud of their knowledge and of searching for new places and possibilities.

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Goal



Issue

- Most of the works use **unsupervised techniques, K-means**
 - to determine which player type fits better for a specific user, based on his/her mapped characteristics
 - However, these approaches usually get data from an already finished game, not having an algorithm ready for improvements in mechanics or difficulty.

Solution

- A combination of **K-means** + **Decision Tree algorithms** + **Bartle Taxonomy**

Solution

- A combination of **K-means** + **Decision Tree algorithms** + **Bartle Taxonomy**
 - Want to label each centroid, applying known archetypes to them.
 - to make this classification update regularly during the gameplay
 - This approach allows us to change the game mechanics and difficulty, having new centroids and decision trees for each newly added session
 - Allow programmers and designers to understand the classification steps quickly, e.g., which attribute was more decisive for each group.

Bartle's Taxonomy

- In this work (a single player shoot'em up games)
 - Achievers, who focus on collecting items and coins
 - Killers, who focus on killing enemies
- Combined with
 - Casual
 - Hardcore

Dataset

- A0) Number of direction changes (Mean);
- A1) Position in X axis (Mean);
- A2) Position in Y axis (Mean);
- A3) Total time in movement (Mean);
- A4) Number of items collected (Total);
- A5) Number of coins collected (Total);
- A6) Number of destroyed enemies (Total);
- A7) Percentage of game completed (Total);
- A8) Number of shots (Mean);
- A9) Number of shots on target/enemies (Mean);
- A10) Number of shots without enemies (Mean);
- A11) Number of shots taken or
Number of lives lost (Total);



We define twelve attributes that are updated every half a second (0.5 second is the time interval).

Algorithm

1. Applied K-means clustering with $K=4$
2. Assigned C0, C1, C2, C3 to each instance.
3. Applied Decision Tree

Decision Tree

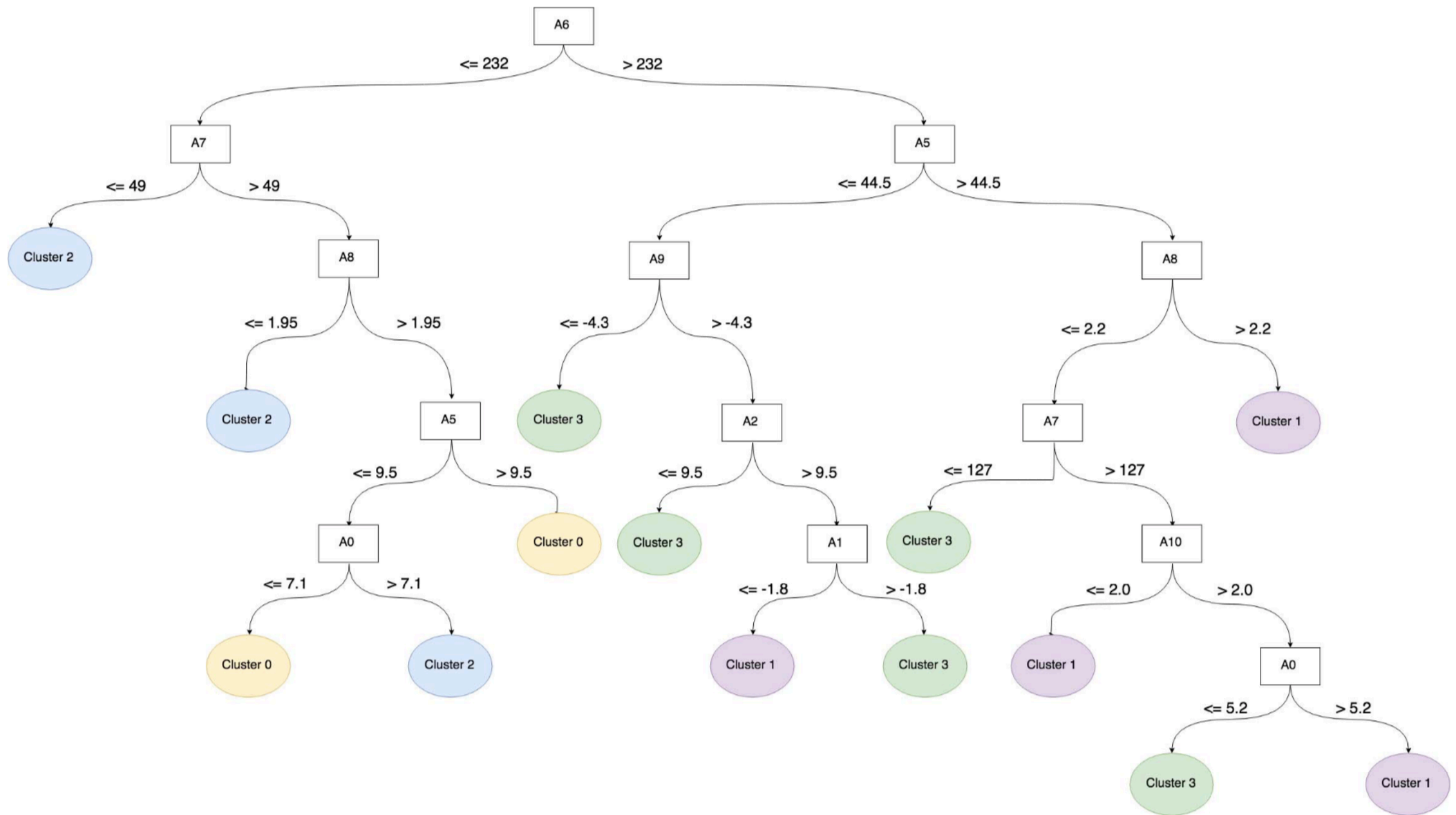


Figure 6. Decision Tree generated by *Accord.NET* algorithm

Algorithm

1. Applied K-means clustering with $K=4$
2. Assigned C_0, C_1, C_2, C_3 to each instance.
3. Applied Decision Tree
4. This paper select A_5 , and A_6
5. Now we could iterate in the centroids array $[C_0, C_1, C_2, C_3]$, searching which one of them had the bigger A_5 value. This first one would be the “**Hardcore Achiever**” centroid. Then we would search, among those remained, which one had the bigger A_6 value. This second one would be the “**Hardcore Killer**” centroid. This same process was repeated for the rest of the array, choosing, respectively, the “**Casual Achiever**” and the “**Casual Killer**” centroids.

**To cross check with
real player's profile**

Questionnaire Design

We designed two questionnaires.

- The first verifies if the player is classified as an **Achiever** or a **Killer**. It was based on the work by Schneider et al. (2016), which presents a questionnaire containing twenty questions, resulting in a percentage for each player type.
- Not use binary questions forcing the player to fit in a profile (e.g. one answer indicates an achiever profile and the other a socializer one)
 - They use, instead, the same five answers for every question:
 - “I do not understand/I do not identify myself” (0 points);
 - “I identify myself a little” (1 point);
 - “I identify myself partially” (2 points);
 - “I identify myself” (3 points);
 - “I identify myself totally” (4 points).

Questionnaire Design

- Achiever
 - “I like to conquer new badges in games”;
 - “I get impressed with players that conquered high rewards”;
 - “I play electronic games until the end with 100% of achievements”;
 - “I love new items and medals”;
 - “I like exposing my achievements (for example, on Facebook)”.
- Killer
 - “I am very competitive in games”;
 - “I like exploding things in games”;
 - “My favorite games are first person shooters”;
 - “I am known for my aggressiveness in games”;
 - “I do not like talking in games, what I really like is shooting”.

Achiever or Killer

To decide whether the player is an Achiever or a Killer, we decided to sum the points related to the questions of each archetype, and get the maximum value from their result, as shown in equation 3. If the sum result is equal for both types, the player is classified as both, lowering the chances of the game classification being wrong. This also happens, for instance, if the player is defined as 55% Killer and 45% Achiever, i.e. he/she is classified as both if the distance between both Killer and Achiever percentage is below or equal to 10 percentage points.

$$PT = \max \left(\sum_{i=1}^5 A_i, \sum_{j=1}^5 A_j \right), (A_i, A_j) \in [0, 4] \quad (3)$$

Casual or Hardcore

- “I always deal with technology and seek for new releases and trends” (7 points);
- “I like to have the latest high-end computers/consoles” (7 points);
- “I’m willing to pay anything for a game” (5 points);
- “I prefer violent/action games” (1 points);
- “I prefer games that have depth and complexity” (3 points);
- “I play games over many long sessions” (10 points);
- “I always search for the game industry latest information” (6 points);
- “I frequently talk about games, both via social media and with people” (10 points);
- “I always feel happy when completing (or defeating) a game” (7 points);
- “I don’t get easily frustrated while playing a game” (9 points);
- “I am usually engaged in competition with myself, the game, and other players” (6 points);
- “I started playing games when I was little” (2 points);
- “I have played all the types of game genres, and I constantly compare one game to another” (10 points);
- “I buy games and consoles on their pre-release, or import them from other countries to be one of the first to play” (9 points);
- “I think of modifying and extending some of the games I play” (8 points);

Casual or Hardcore

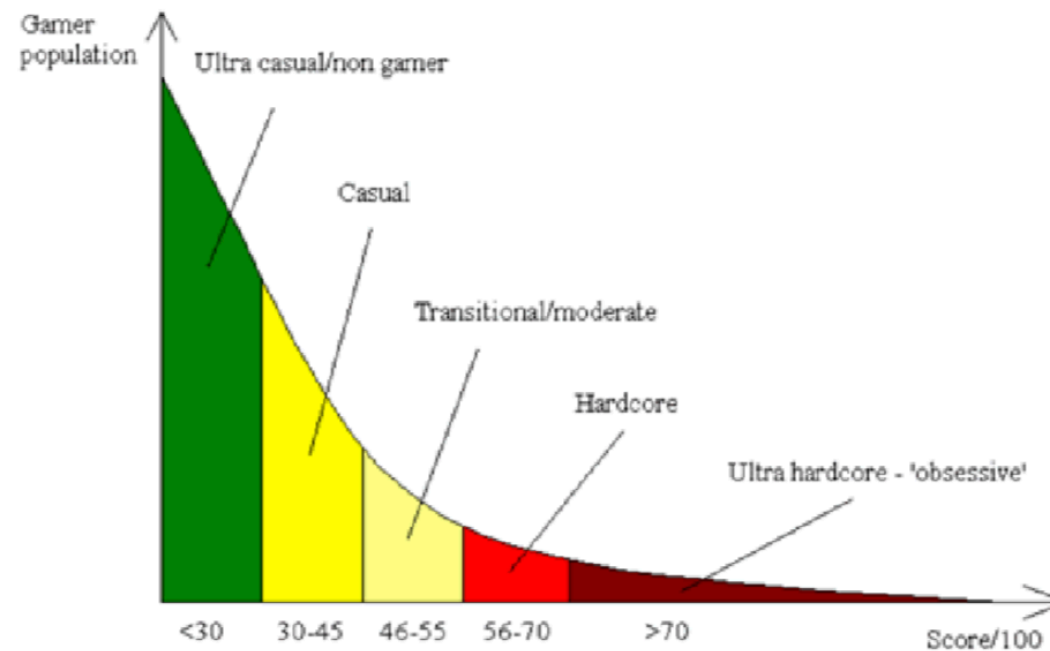


Figure 7. Casual and Core by gamer dedication

- 1) Casual gamer - Has GD factor below or equal to 45%;
- 2) Moderate gamer - Has GD factor between 45% and 55%, with these limits included;
- 3) Hardcore gamer - Has GD factor above 55%.

$$GD = \frac{\sum_{i=1}^{15} A_i \times Q^i}{\sum_{i=1}^{15} 5 \times Q^i} \quad (4)$$

Results

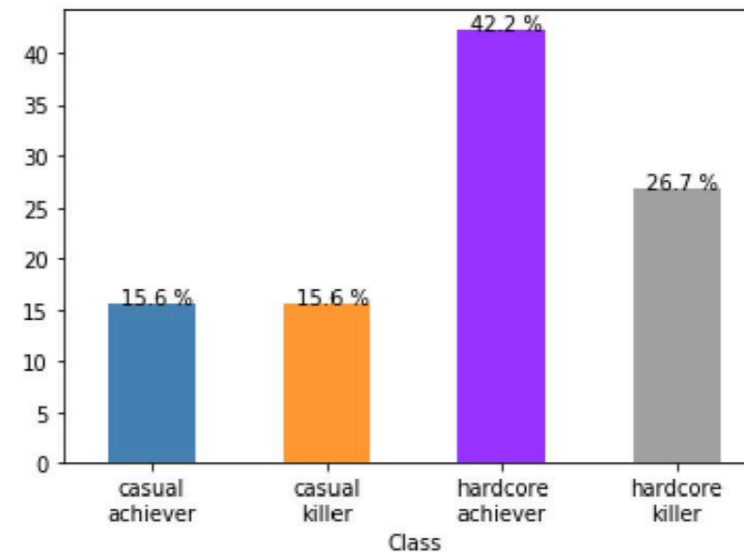


Figure 8. Total of each archetype found on game sessions

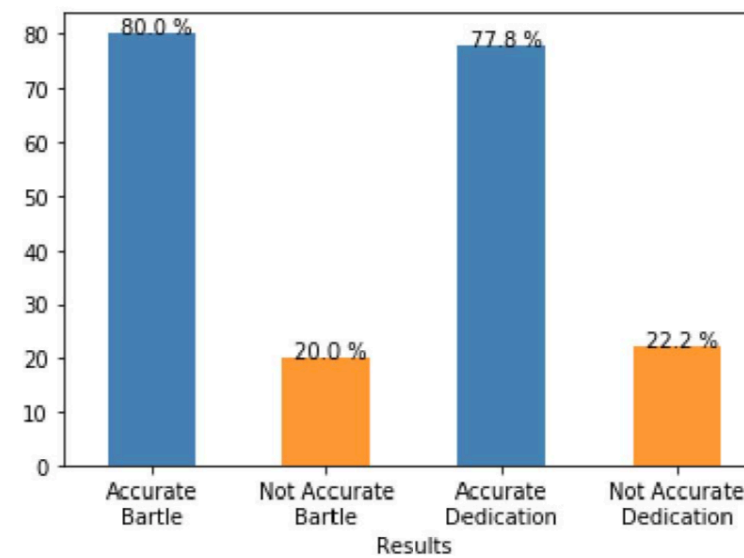


Figure 9. Accuracy results for both dedication and Bartle archetypes

Future works

Our approach allows the creation of an adaptive model, which would base itself on the player classification to vary the difficulty of the game, changing parameters like

- enemy speed,
- the number of enemies on screen,
- enemy fire rate,
- player fire rate, and
- other relevant gameplay characteristics.

There are many future works to do. We should investigate if player type scores do significantly predict player experience.