Guns and Guardians: Comparative Cluster Analysis and Behavioral Profiling in *Destiny*

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***Abstract*— Behavioral profiling in digital games with persistent online worlds are vital for a variety of tasks ranging from understanding the player community to informing design and business decisions. In this paper behavioral profiles are developed for the online multiplayer shooter/role-playing game *Destiny*, the most expensive game to be launched to date and a unique hybrid incorporating designs from multiple traditional genres. The profiles are based on playstyle features covering a total of 41 features and over 4,800 randomly selected players at the highest level in the game. Four clustering models were applied (k-means, Gaussian mixture models, k-maxoids and Archetype Analysis) across the two primary game modes in *Destiny*: Player-versus-Player and Player-versus-Environment. The performance of each model is described and cross-model analysis is used to identify four to five distinct playstyles across each method, using a variety of similarity metrics. Discussion on which model to use in different circumstances is provided. The profiles are translated into design language and the insights they provide into the behavior of *Destiny*'s player base described.**

I. INTRODUCTION

The analysis of player behavior in digital games has, with the introduction of telemetry tracking and game analytics, become a cornerstone of game development. Behavioral analysis assists across all phases of a development cycle as well as after launch, and can help with a variety of tasks from balancing, experience evaluation, cheat detection, prediction, monetization and debugging [7]. One of the key behavioral analyses that has emerged in the nascent domain of game analytics in the past five years is behavioral profiling [6], [1].

Behavioral profiling is a technique known from a variety of data and information science domains, including web analytics and finance, and serves as a means for considering users or consumers in a non-abstract and quantifiable way. Behavioral profiling in digital games seeks to condense the often high-dimensional, high-volume and volatile behavioral datasets generated, notably typical for major commercial (AAA) titles, into a subset of well-described profiles that encapsulate player behavior and informs game developers and researchers about how people are playing the game under investigation. This location of patterns in the behavior of players is a major challenge in game analytics, as well as the construction of actionable models based on patterns.

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Behavioral profiling in games has previously been performed using a variety of descriptive and statistical techniques, as well as machine learning, the latter with an emphasis on unsupervised techniques due to the common explorative goal of profiling in games [8], [2], [22].

One of the most popular approaches has been clustering [10], [6]. Cluster models allow segments to be developed which can describe the behavior of players according to specific behaviors and are driven by specific research questions. For example, discovering major playstyles in a game. Clusters can be translated into descriptions of the different player segments, and the information contained within can inform the game design and optimization [1], [11]. However, there are a great number of cluster models available, each with specific strength and weaknesses, and it can be challenging to assess which algorithm to employ in a given situation.

The analysis of player behavior is important to any digital game but is notably important in persistent online games, as the success of these games rests on their ability to keep a player community engaged over extended periods. It is increasingly common for games to feature persistent gameplay, as it enables the application of sources of revenue not available under a retail-based model [12]. This is also the case for *Destiny*, a hybrid online game that combines elements from a number of game genres, with a primary emphasis on online shooter-type gameplay. The game was released in 2014 as a console-exclusive title. Players take on the role of a guardian, a warrior who works to fend off alien forces attacking Earth. In this paper four different cluster models are applied to detailed behavioral telemetry from *Destiny*, focusing on player performance, for the purpose of developing behavioral profiles for the game, as well as for evaluating the models themselves.

II. CONTRIBUTION

In this paper, behavioral profiles are presented for the online multiplayer shooter game *Destiny*. The game forms a hybrid between a shooter game and Massively Multiplayer Online Game (MMOG), and thus presents a game format that has not previously been explored in game analytics. Behavioral profiles are developed based on cluster analysis for a subset of 41 behavioral features engineered from a dataset of over 1,400, focusing on performance and playstyle measures but including others. Profiles are developed for both of the two primary game modes: Player vs. Player (PvP) and Player vs. Environment (PvE), and include more than 4,800 players, all randomly sampled from the pool of players at the maximum character level. Four clustering models are applied to the data: Archetype Analysis (AA), k-means, k-maxoids, and Gaussian mixture models (GMM), each resulting in prototype players or centroids that are representative of different clusters of behavior.

The results of each model are described and compared, and the strengths and weaknesses of each method described. This informs future work in industry that seeks to build behavioral profiles in games, and highlights the importance of balancing feature selection, choice of model and the interpretability and actionability of the resulting behavioral profiles. Feature engineering in an ultra-high dimensionality situation like *Destiny* is also discussed. Finally, the behavioral profiles developed are described in terms of design language, following the principles of Drachen et al. [8], and their insights into player behavior in *Destiny* discussed.

III. DESTINY: GAMEPLAY

Destiny is a science-fiction themed game where players take on the role as Guardians, who defend the Earth in a future where there is only one safe city left, and the human race is threatened by alien powers. Players protect the city from these alien races, and are tasked with the overall goal of reviving a Moon-sized being called the Traveler, who protected the human civilization but now lays dormant. To do this the players must explore a variety of planets, complete various missions and help eliminate the alien threat.

Destiny is a hybrid digital game that blends features from a number of traditional game genres. *Destiny* is first and foremost an online first-person shooter (FPS) game, and the majority of the gameplay is focused on using any of thousands of different weapons to eliminate either computer-controlled or human opponents. Other examples of online FPS games include *Planetside 2*. As an FPS, *Destiny* features both single-player and multiplayer game modes, as well as both Player-vs-Environment (PvE) and Player-vs-Player (PvP) combat. PvE mode includes a variety of story missions, usually given by NPCs in the game's central quest hub "Tower", but also includes public events, raids and strikes, which require three or six players respectively to collaborate in "fireteams" of 3. When playing in fireteams, players can put themselves at risk and revive a teammate.

In terms of the MMOG elements, *Destiny* features a persistent, shared world in which the players interact with each other and Non-Player Characters (NPCs). The game has its own currencies, factions players can build reputation with, and a comprehensive item customization system, all common features in MMOGs. The game has missions/quests, delivered by NPCs, which covers a range of different activities. The game also features social interaction, although the communication options are more restrictive in *Destiny* as compared to MMOGs. As a Role-Playing Game (RPG), *Destiny* features character classes (Hunter, Warlock and Titan, each with three subclasses), experience points, character development and unlocking of more powerful items and abilities as players progress from level 1 to 40, which is the current level cap. As a Multiplayer Online Battle Arena (MOBA) game, *Destiny* features team-based combat within arena-type environments, similar to e.g. *League of Legends*.

PvP play is done via the *Crucible*, the central hub for this game mode. There are a variety of different specific modes, including traditional deathmatch modes, take-and-control modes, and more. In PvP players can earn medals, points and in-game currency by accomplishing specific tasks or feats of skill. For example, a "First Blood" medal awards extra points to the player with the initiative to get the first kill in a match. In both PvE and PvP game modes, players are rewarded with new weapons and items through random drops or by completing specific tasks.

Another key aspect of *Destiny* in both the PvE and PvP modes is weaponry. *Destiny* features hundreds of different weapons (ranged and melee), which can fire a variety of energy types or projectiles, and be customized in innumerable ways. Together with armor and ships, guns are perhaps the focal point of development in the game. Weapons are divided into over a dozen different types or classes, each specialized for specific situations. For example, shotguns excel in close-quarters combat, dealing large amounts of damage with little need to precisely aim. Conversely, sniper rifles offer similar amounts of power but are rendered near useless when the target gets too close. Even at the optimal distance, however, they require skilled players who can aim precisely. Between game modes, the utility of these weapon types also varies; shotguns are typically a one-shot kill in PvP modes, but must be used with care in PvE modes, as enemies with large health pools can quickly strike back with devastating close range attacks. Players are given freedom to switch between any combination of weapon types, allowing for adjustment to in-game scenarios while at the same time reflecting individual behavior and preferences.

IV. RELATED WORK

There are a number of challenges associated with behavioral telemetry data in digital games, notably that they are commonly large-scale, high-dimensional and volatile [6], [1]. This is also the case for *Destiny*, and is exemplified in the current dataset which contains over 1,400 baseline features, based on just one of a dozen JSON collections. While only a subset of the population is used here due to data size constraints, *Destiny* has dozens of millions of active players, requiring the adoption of random selection when defining samples. Given the constant changes in the design of the game via new content and tweaks to the mechanics, as well as the running turnover in the population of the players, any profiles generated will have a limited lifetime during which they are accurate representations of the underlying player base. Pattern recognition under the conditions of contemporary commercial game development can thus be difficult, but also potentially highly rewarding because such patterns directly inform the game development process, can be used for Game AI related purposes, or to personalize or adapt gameplay, assist matchmaking, and identify valuable players [6], [8], [15], [1], [16], [17]. Cluster analysis [10] is one of the primary tools available for pattern recognition and has been readily applied across disciplines, and even in recent years adopted in game analytics for the purpose of finding patterns in the behavior of players. As an unsupervised method, it permits the exploration of data and can identify groups of players with similar behaviors or detect the features that constitute such behaviors [6], [8], [15], [1], [16], [17].

The popularity of cluster models in explorative evaluation of behavior is in part driven by the wide variety of models, which can be applied to reach specific outcomes, e.g. searching for extreme or central tendencies in the data [1], [6], [10].

The majority of previous work on behavioral profiling in games has focused on employing specific methods, with the only work specifically comparing multiple cluster models being Drachen et al. [2] who applied k-means, c-means, Non-negative Matrix Factorization (NMF), Archetype Analysis (AA) and Principal Components Analysis (PCA) for a dataset covering player character progression in *World of Warcraft*, and noted the different output produced by these models but did not discuss cross-model analysis. Bauckhage et al. [6] showed examples of multiple models and advised on their application. This paper directly extends on this previous work by comparing four cluster models and specifically targeting the problem of making decisions across models.

Behavioral profiling via clustering, and related methods, has been performed using a variety of models (the following are more or less in order of publication): The first paper to target the profiling problem was Drachen et al. [8], who used Self-Organizing Networks in combination with data from 1,365 players of *Tomb Raider: Underworld*. The authors documented that over 95% of the players could be allocated to one of four behavioral profiles. In a follow-up piece, by Sifa et al. [11] who explored how player profiles varied as a function of progress in the same game.

Shim and Srivastava [16] used segmentation and descriptive methods to examine the behaviors of *EverQuest II* players, focusing on behavioral profiling and efficiency in player behaviors. Thurau and Bauckhage [18] explored the evolution of guilds in *World of Warcraft*, across 18 million characters using matrix factorization. Thawonmas and Iizuka [17] used multidimensional scaling (CMDS) and KeyGraph to generate visualizations of player clusters working with the MMOG *Shen Zhou Online*. Drachen et al. [1] employed Simplex Volume Maximization (SIVM) and k-means on datasets from the MMOG *Tera: Online* and the team-based shooter *Battlefield 2*, developing behavioral profiles for these two games based on a range of behavioral features. Sifa et al. [19] analyzed more than 3,000 games and over 6 million players from the distribution platform Steam to investigate playtime patterns, and developed clusters of games via Weibull modeling. The work was followed up by Sifa et al. [20] who identified 11 clusters of players based on their relative playtime distribution across games on Steam.

Bauckhage et al. [21] adopted DEDICOM (Decomposition into Directional Components) to cluster players of *Quake: Arena* and develop waypoint graphs for behavior-based partitioning. Normoyle and Jensen [22] used Bayesian Clustering on data from the multiplayer shooter game *Battlefield 3* covering over 500,000 matches. In the multiplayer esports game *DOTA 2*, Drachen et al. [24] clustered players according to spatio-temporal behavior and skill, using distance measures and k-means. Finally, Sifa et al. [23] adopted DEDICOM to investigate player churn behavior among multiple games.

V. DATA AND PRE-PROCESSING

For this study, two distinct sets of data from the game *Destiny* were used: PvP, and PvE. The data was provided as a large JSON object, which was parsed and converted into a flat comma delimited file. The data is aggregated and exists on a static level, meaning for each character there is a slice of data only at the point in time when the data was pulled. If the character has progressed since (e.g. changed weaponry, made more kills, leveled up), the information is not reflected in the data. Similarly, the characters details when they started the game (e.g. weapon equipped in the first five minutes, number of kills in the first five minutes, level during the first five minutes), is also not reflected in the data.

A. PvE Dataset

- Consists of 1,217 variables detailing encounters by 27,967 player characters in the game.
- Divided into five categories:
- Basic character information containing the account ID and character ID field, and the deleted flag, showing whether a character has been deleted or not. The information covers virtually any aspect of player behavior across performance, engagement, progression, etc.
- Game Progress variables detailing how many activities the character has participated in and completed.
- Personal bests of kills and deaths.
- Average statistics of kills and deaths.
- Total counts of kills and deaths.

B. PvP Dataset

- Consists of 211 variables detailing encounters by 16,422 characters in the game.
- Divided into five categories:
- Basic Character information containing Account ID and Character ID, and the deleted flag, showing whether a character has been deleted or not.
- Game Progress variables detailing how many activities the character has participated in and completed.
- Personal bests of kills, deaths, and medals earned.
- Average statistics of kills, deaths, and medals earned.
- Total counts of various kills, deaths, and medals earned.

C. Behavioral Features and Selection

Clustering analysis relies on being able to classify players into groups based on features. Conversely, the features used for clustering should easily explain the groupings that are found [8]. To this end, it is important to filter out highly specific, correlated, redundant, and dependent variables, which may create noise and obfuscate the end results. In order to keep the clusters decipherable, feature selection, with an emphasis on finding the subset of variables that explain overall variation in the dataset is necessary. Feature selection was done based on classifying the available high-level variables into three categories: performance, progress, and playstyle. Here the focus is on developing high-level profiles and thus the playstyle features covering *Destiny*'s main mechanics were used. The initial selection process yielded 41 features from the original over 1,400. Initially, about 90% of of the PvE variables were removed due to redundancy. This paper focuses on high-level behaviors, so highly specified features are excluded, as the information is better contained and summarized by higher level aggregate features. For example, the original data kept track of how many times a player was killed by a specific enemy in a particular encounter of one mission in the game. Additionally, many attributes depended directly on a players time spent playing the game. To mitigate this effect, a subset of characters that had already reached the games level cap of 40 were considered in the analysis (4,800 players) (Fig. 1).

Features	PvP Mean	PvP St. Dev.	PvE Mean	PvE St. Dev.
Average Kill Distance	13.80	3.66	18.15	3.23
Proportion of Kills using Auto Rifle	12.25%	13.25%	16.1%	11.0%
Proportion of Kills using Fusion	4.57%	7.38%	3.6%	3.0%
Proportion of Kills using Grenade	6.49%	3.82%	7.1%	2.5%
Proportion of Kills using Hand Cannon	9.27%	9.86%	12.0%	9.3%
Proportion of Kills using Machine Gun	3.19%	3.30%	1.7%	1.2%
Proportion of Kills using Melee	11.40%	7.49%	12.5%	4.8%
Proportion of Kills using Pulse Rifle	7.44%	9.02%	9.4%	7.6%
Proportion of Kills using Rocket Launcher	2.73%	2.54%	3.4%	2.4%
Proportion of Kills using Scout Rifle	4.91%	7.92%	15.1%	10.4%
Proportion of Kills using Shotgun	12.25%	9.51%	3.6%	2.9%
Proportion of Kills using Side Arm	0.70%	2.64%	1.0%	1.4%
Proportion of Kills using Sniper	4.07%	5.24%	4.5%	2.8%
Proportion of Kills using Super	11.83%	6.48%	4.9%	2.7%
Proportion of Kills using Sword	1.01%	3.02%	1.3%	1.9%
Proportion of Kills using Relic	N/A	N/A	1.3%	1.3%
Proportion of Games earning First Blood	1.70%	1.28%	N/A	N/A
Proportion Offensive Kills	4.57%	2.97%	N/A	N/A
Proportion Defensive Kills	4.07%	2.55%	N/A	N/A
Avg Time Remaining after Quitting (sec)	33.50	320.76	N/A	N/A
Proportion of Games played in PvP	18.77%	14.06%	N/A	N/A
Max Proportion of Kills with a Weapon	N/A	N/A	26.4%	9.1%
Orbs Dropped Per Sec	N/A	N/A	0.01	0.002
Resurrections Performed / Received Ratio	N/A	N/A	1.1	0.5

Fig. 1. Mean and standard deviation of the primary features in the PvP and PvE datasets from *Destiny*.

An exploratory data analysis was performed on the remaining features, including histograms and correlation analysis. Correlation analysis revealed that many attributes exhibited large correlations with play time. For example, the raw number of recorded kills per weapon understandably increased over time. Weapon kills were time normalized after being converted to a proportion of total kills. Other variables that had no associated total amount with which to calculate a proportion were converted to a rate by dividing by the number of seconds played. Histogram plots revealed significant right skew in many of the attributes. To account for this, a logarithmic transformation was applied. Some skew still remained after applying these transformations, so zero mean standardization was applied to ensure that all variables were on the same scale. After correcting for the aforementioned skewness and time dependencies, the final selection of variables involved creating a set of attributes designed for all of the main game mechanics in either mode.

VI. CLUSTER MODELS

Four different clustering methods were applied to the data. Each clustering methodology had a variety of parameters to choose from, such as number of clusters or archetypes, and cluster shapes. To account for the inherent differences in how the methods generate clusters, different evaluation metrics were chosen for each method to determine the optimal number of clusters. The optimal cluster solutions for each method were compared using adjusted mutual information. The four models are as follows:

A. K-means Clustering

The k-means algorithms partitions the data in k different clusters such that all points in a given cluster are closest to the corresponding cluster center. K-means is a common clustering method in game analytics, for example in Drachen et al. [1] and Drachen et al. [2]. While more computationally efficient than the algorithms mentioned below, k-means focuses on the average behavior of players and does not identify more extreme behavior accurately. Additionally, resulting k-means clusters must be spherical in shape and the algorithm is biased to equal-sized clusters. However, the algorithm can still be used to observe and cluster the general average behavior of players in *Destiny*, serving as a baseline to support the findings of other methods, such as Archetype Analysis, that are designed to identify more extreme behavior. The k-means function in R was used to cluster PvP and PvE players based on the various playstyle metrics. In order to select the best number of clusters, a natural grouping was assumed to be homogenous within and heterogenous across, i.e. the solution should have a high between-cluster variance and a low within-cluster variance. The best solution, in terms of interpretability and using the aforementioned metric, resulted in a four cluster solution.

B. Gaussian Mixture Models

Gaussian mixture models are conceptually related to k-means clustering, with a few distinct differences. First and foremost, k-means clustering assumes that each cluster is approximately equally sized and distributed–that is, there will be an approximately equal number of data points within each cluster, and each cluster will appear to be a sphere of equal proportions to the other clusters. Gaussian Mixture Models, on the other hand, relax this constraint; the user has control over whether to enforce equal sizes of clusters as well as whether or not to assume a spherical shape, as opposed to an ellipsoidal shape. When using ellipsoidal clusters, the ellipsoids can either all be oriented in the same direction, or always oriented along the coordinate axes; or, if necessary, the orientation can be in any direction. This allows for more flexible definitions of clusters. For more information on the math behind Gaussian mixture models, see [14].

For the purpose of this analysis, the R statistical software package Mclust was used thanks to its flexibility and available features [13]. Mclust was able to return the results of all possible model shapes as well as a range from one cluster to ten clusters. Based on the Bayesian Information Criterion (BIC), Mclust selects the best shape and number. The best result based on this criterion used four ellipsoidal, equally-sized, and equally-oriented clusters for PvP, and six ellipsoidal, equally-sized, and equally-oriented clusters for PvE. While Gaussian mixture models have not been known to be used in previous work in game analytics, it was included in the analysis for its similarity to k-means, and to provide an opportunity to examine the similarities between two centroid-based methods.

C. Archetype Analysis

Archetypal Analysis seeks to identify points whose convex combinations can generally represent the population of the dataset. These archetype points are not necessarily observed, but exist as manifestations of extreme behavioral qualities. This means that archetypes typically exhibit more radical values than the typical observation. Each observed data point is then classified to its closest archetype, resulting in clusters. Archetype Analysis [4] has previously been used for game analytics by Sifa et al. [3]. In contrast to centroid-based clustering algorithms such as k-means and Gaussian mixture models, the clusters found using archetypal analysis are identified by prototypical points. This means that the contrast between various archetypes is magnified (more so than the mean of these clusters), as they represent more extreme values. Conversely, this means that the values that are less extreme get classified to these clusters. A Scree plot using residual sum of squares (RSS) found that the optimal data groupings were four clusters for PvP and five for PvE.

D. K-Maxoids

Similar to archetype analysis, k-maxoids seeks to find cluster prototypes that represent the extremes of a data set rather than the modes. The maxoid of a set is defined as a data point that has the largest average distance from all other points in the same set. Bauckhage and Sifa [5] used the method in the context of game analytics to cluster players based on vehicle usage. Due to the extreme nature of the maxoids, the resulting cluster prototypes are generally more varied than those produced by centroid-seeking algorithms such as the Gaussian mixture models and k-means. To choose the optimal number of clusters, the average silhouette score was computed for cluster sizes ranging from three to eight. The four cluster and five cluster solutions were chosen as the best for PvE and PvP, respectively.

VII. EVALUATING CLUSTER SIMILARITY

Each clustering method produced a somewhat different set of clustering classifications, which begs the question, how different are these clusters, and how does it affect the results? In order to understand how similar one method was to another, clustering results were compared using the Adjusted Mutual Information (AMI) value [Vinh]. AMI ranges on a [-1,1] scale, where 1 is perfectly similar, 0 is no more similar than what would be expected in a random assignment, and -1 is perfectly dissimilar (less similar than a random clustering). Fig. 2 shows the AMI for each method, using cluster sizes of four, five, and six to account for different methods having different preferred numbers of clusters. This directly extends the comparative work of [2]

		Gaussian Mixture Models			K-Means Clustering			K-Maxoids			Archetype Analysis		
		4 Clusters	5 Clusters	6 Clusters	4 Clusters	5 Clusters	6 Clusters	4 Clusters	5 Clusters	6 Clusters	4 Clusters	5 Clusters	6 Clusters
Gaussian Mixture Models	4 Clusters	1	0.6	0.6	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1
	5 Clusters	0.2	1	0.7	0.2	0.2	0.2	0.1	0.1	0.1	0.1	0.1	0.1
	6 Clusters	0.4	0.3	1	0.2	0.2	0.2	0.0	0.1	0.1	0.1	0.1	0.1
K-Means Clustering	4 Clusters	0.1	0.2	0.2	1	0.6	0.5	0.1	0.2	0.2	0.3	0.3	0.3
	5 Clusters	0.1	0.2	0.2	0.6	1	0.8	0.1	0.1	0.3	0.3	0.4	0.3
	6 Clusters	0.1	0.2	0.2	0.3	0.5	1	0.1	0.1	0.3	0.3	0.4	0.4
K-Maxoids	4 Clusters	0.1	0.1	0.1	0.1	0.1	0.1	1	0.6	0.2	0.1	0.1	0.1
	5 Clusters	0.1	0.1	0.1	0.2	0.2	0.2	0.2	1	0.2	0.1	0.1	0.1
	6 Clusters	0.1	0.1	0.1	0.2	0.2	0.2	0.2	0.6	1	0.2	0.3	0.2
Archetype Analysis	4 Clusters	0.1	0.1	0.1	0.5	0.5	0.3	0.1	0.3	0.3	1	0.3	0.3
	5 Clusters	0.1	0.2	0.2	0.4	0.4	0.4	0.2	0.3	0.3	0.4	1	0.3
	6 Clusters	0.1	0.1	0.1	0.3	0.3	0.3	0.1	0.2	0.2	0.4	0.2	1

PvE Similarities

PvP Similarities

Fig. 2. Adjusted Mutual Information for Various Clustering Results. The upper triangle (yellow) represents PvE clustering AMIs, while the lower triangle (green) represents PvP clustering Adjusted Mutual Information values (AMI).

The results were not as expected based on the models employed: the expectation was to see a high degree of similarity between GMM and k-means, since the two methods share a centroid-based approach to clustering. Furthermore it was expected that k-maxoids and Archetype Analysis would be similar due to their mutual reliance on extrema of the dataset. However, from the above chart, the clusters had AMIs that were, for the most part, only slightly above 0 (where 0 implies they were no more similar than a random assignment of classifications). The one exception was between Archetype Analysis and k-means, which can reach as high as 0.6 for PvE and 0.5 for PvE, which suggests the two methods were producing more consistent results than a random assignment would. The lack of similarity amongst either the centroid-based models or the extrema-based models, as well as the moderate similarity between Archetype Analysis and k-means, were contrary to our expectations. A comparison using the Jaccard similarity coefficient yielded comparable results, so only one set of values is included here.

These results suggest that, while no method is necessarily more powerful than any other method, the expectation that each method is interchangeable with any other method is incorrect. As such, it is important to look beyond the quantitative comparisons of each clustering result, and instead focus on the characteristics of the clusters within each result to see which methods produce the most interpretable clusters.

A. Comparing Models Using Cluster Interpretability

The key in any clustering exercise is that, first and foremost, the clusters produced must be valuable to the recipient of the analysis. Clusters may appear in the data but if there are no actionable insights to be gained, the knowledge of those clusters are unhelpful. Because the clustering methods so far have been shown to have low similarity, the expectation was that profiling those clusters (that is, looking at the defining characteristics of each cluster to create a more general set of terminologies by which to consider those clusters) would also return sets of profiles that are different from method to method. Table 1 shows an example heatmap used to identify clusters with Archetype Analysis.

Variable	Archetype 1	Archetype 2	Archetype 3	Archetype 4
Avg Time Remaining after Quitting	-0.5	-1.0	0.8	0.3
Proportion Defensive Kills	2.1	-1.6	0.3	-0.7
Proportion Offensive Kills	1.7	-1.4	0.8	-1.0
Average Kill Distance	0.0	-0.4	-1.9	2.3
Proportion of Kills using Auto Rifle	2.3	-0.4	-0.8	-0.9
Proportion of Kills using Fusion Rifle	0.9	-0.6	0.0	-0.4
Proportion of Kills using Grenade	0.4	-0.6	0.2	-0.3
Proportion of Kills using Hand Cannon	-0.9	-1.0	-0.1	1.2
Proportion of Kills using Machinegun	0.5	-1.0	-0.6	0.7
Proportion of Kills using Melee	-0.2	-0.9	1.6	-1.1
Proportion of Kills using Pulse Rifle	-0.8	1.1	-0.8	0.7
Proportion of Kills using Rocket Launcher	-1.0	-0.9	0.3	0.9
Proportion of Kills using Scout Rifle	-0.6	1.2	-0.5	-0.1
Proportion of Kills using Shotgun	-1.3	-0.4	1.7	-0.6
Proportion of Kills using Side Arm	-0.2	0.7	-0.2	-0.2
Proportion of Kills using Sniper	-0.5	-0.7	-0.8	2.4
Proportion of Kills using Super	-0.1	1.2	-0.3	-0.6
Proportion of Kills using Sword	-0.3	1.4	-0.3	-0.3
Proportion of games earning First Blood	-0.5	-1.1	0.2	0.8
Proportion of games played in PvP	-0.9	-1.1	0.4	1.4

Fig. 3. Example heatmap used to identify clusters with Archetype Analysis. Each archetype has different prototypical values associated with each variable, which were used to differentiate and profile the archetypes. Red values indicate values below the mean, and blue values indicate values above the mean for each variable (the strength of the hue helps to show which clusters have the most extreme values for each parameter).

Each method, having produced a single best set of clusters based on the aforementioned criteria for cluster selection, was subjected to an exercise by which a title was assigned to each cluster based on its profile. Tables 1,2 show two sample results of for PvP, and tables 3,4 for PvE.

B. PvP

For the PvP dataset, the two largest clusters identified by Archetype Analysis, using a four-clusters solution as shown in Table 1, are groups that are characterized by their use of specialized weapons: *Aggressive Close Range* players make effective use of Shotguns and complement their favorite weapon with melee blows in order to dismantle PvP opponents. The second largest group, *Marksmen*, make use of sniper rifles to take out opponents at a long range and make smart use of hand cannons to take out enemies that are at a close to medium range. *Objective Killers* are players that play a majority of Control games where the match consists of holding various bases, defending them and attacking enemy-controlled bases. Finally, *Casual PvPers* are individuals that play a higher proportion of PvE that are not focused on using any specific weapon type. Because these archetypes are defined using the extreme values in the dataset, the differences between cluster values tend to be more dramatic. These more pronounced differences lead to clusters that are more distinguishable from one another.

TABLE I

PvP Profiles for Archetype Analysis. %P = % of players

Title	%P	Characteristics
Objective Killers	20.1	Highest scores for proportion offensive & defensive kills
Casual PvPer	15.9	Does not appear to play PvP much
Aggressive Close Range	35.1	Lowest average kill distance, highest melee and Shotgun kills
Marksmen	28.9	Highest average kill distance, highest Hand Cannon and Sniper usage; plays PvP the most

Table 2 shows the clusters identified by Gaussian mixture models, using a 4 cluster solution. However, only the long-range hardcore PvP cluster can be readily interpreted. The short-range kill distance with long-range weapons used cluster is counter-intuitive. There does not not seem to be a logical explanation for why 14.2% of players prefer weapons intended for medium-long range to kill opponents at short range, but it may be an effect of less experienced players not yet proficient with weapon switching, possibly being recent lvl 40 characters. The two last clusters include almost 70% of all players included in the clustering analysis and represent what would be a balanced playstyle. Gaussian mixture models do not perform well here because the method identifies and groups players based on the average behavior of all individuals, a pitfall shared by k-means. The cluster results exist closer to each other at the center of the data, leading to prototypes with less pronounced differences.

TABLE II

PvP Profiles for Gaussian Mixture Models. %P = % of players

Title	%P	Characteristics
Short-range with long-range mix	14.2	Lowest average kill distance, but with lower than average use of all typically short-range weapons, and higher than average use of scout rifle (the second-longest range weapon)
Long-range hardcore PvP	16.1	Higher than average fusion rifle usage but otherwise unremarkable; slightly more PvP play than average
Balanced I	37.4	Slightly stronger focus on PvP, with a preference for long-range weapons but also shotguns
Balanced II	28.9	Lower than average sidearm and sword usage, with slightly low PvP playtime, but otherwise unremarkable

C. PvE

Clusters found by Archetypal Analysis in Table 3 were roughly equal in size and were the most readily interpretable in terms of in-game behavior. The archetypes are: *High DPS, Guerilla Warriors, Close Combatants, Sitting Duck Snipers* and *Mobile Marksmen*. These groupings are primarily defined by damage output, distance from enemies and weaponry used. The largest cluster of players focused on using weapons with a high damage per second (DPS) output, and are named *High DPS*. Solely distance-based metrics defined the Close Combatants, who focus on a variety of close combat weaponry and have the shortest average kill distance. Solely variety of weaponry metrics defined the *Guerilla Warriors*, who are a family of players who are highly adaptable to changing situations, and have the highest variety of weaponry used. A combination of distance-based metrics and variety of weaponry metrics established the *Sitting Duck Snipers* and *Mobile Marksmen*. *Sitting Duck Snipers* are a group who prefer to shoot from a single location, utilizing snipers at first and switching weaponry as enemies come closer. In contrast, *Mobile Marksmen* are players who prefer to stick to a single weapon and move themselves as enemies get closer.

TABLE III

PvE Profiles for Archetype Analysis. %P = % of players

Title	%P	Characteristics
High DPS	23.5	Players who appear to focus on high DPS moves (such as specials)
Guerilla Warriors	16.7	Players who often switch weaponry to fit the occasion; highly adaptable, and play a lot of PvP
Sitting Duck Snipers	18.8	Players who are more prone to shoot from a single location and switch weaponry as the enemy closes in
Mobile Marksmen	18.1	Players who stick to using a weapon of choice (Pulse Rifles) and move around to maintain distance when fighting enemies

TABLE IV

PvE Profiles for Gaussian Mixture Models. %P = % of players

Title	%P	Characteristics
Pulse Rifle & Sword Reliant	5.5	High usage in pulse rifles and swords, but no other stand-out qualities
Auto Rifle Reliant	29.4	High usage of auto rifles, low scout rifles, but no other stand-out qualities
Mobile Marksmen	28.1	Highest average kill distance; high usage of scout rifle
High Variety	7.7	Lowest reliance on any single weapon type
Sitting Duck Snipers	21.2	High sniper but mid-range average kill distance suggest a player unwilling to adapt to surroundings
Close Combatants	8.2	Shortest kill distance and reliance on short-range weapons and melee

Table 4 shows prototypes derived via Gaussian mixture models. In this case, the commonalities are the *Mobile Marksmen*, *Sitting Duck Snipers*, and *Close Combatants*, though the proportions of each differ significantly. The combination of features defining the behavioral profiles here titled *Pulse Rifle & Sword Reliant, Auto Rifle Reliant* and *High Variety* proved difficult to interpret in the context of the mechanics in *Destiny*. What the former three clusters have in common is that they all are defined by a set of weapons that seem to be consistent with the average kill distance, which creates an easily interpreted cluster. On the other hand, the other three clusters share the characteristic of being defined by only one or two weapons with nothing else that stands out in great detail.

VIII. Results and Discussion

Destiny provides a number of challenges to the task of developing behavioral profiles, including the sheer variety and volume of this player telemetry data which complicates the feature selection process. To align with the goal of creating high level behavioral clusters, overly specific features can be systematically excluded. A second level of filtering requires knowledge of *Destiny*'s mechanics, and targets features that cover primary gameplay. Lastly, care must be taken to isolate game modes with different gameplay, e.g. PvP and PvE.

The results reveal that the primary differentiators of character behavior fall into three dimensions: a) the usage frequency for different weapons, b) the average kill distance, and c) the time spent playing either PvP or PvE. The first of these two dimensions typically align with each other; players getting more frequent kills with typically longer range weapons tend to have larger average kill distances. Given that *Destiny*'s main gameplay revolves round the collection and upgrading of weapons, the importance of kill frequency by weapon type is understandable, as players may latch onto certain weapon archetypes early in the game and develop their own signature loadout. Some clusters, however, display a wide variety of weapon usage, suggesting that a portion of the playerbase favors a more dynamic loadout and is willing to adapt to various situations in different game modes by changing their weaponry. The game type dimension groups the cluster results into either PvP focused or PvE focused, with few players spending equal time in both. Within each game type, other features serve as proxy measures for activity preferences. For example, offensive and defensive kills are exclusive to the control gametype, in which teams guard territory to earn points, so clusters with large values for these features may correspond to players that prefer objective-based gameplay.

With respect to weaponry, *Destiny* players tend to focus on either only a few or a variety of weapon types. Regardless of game mode, clusters of players emerge that prefer either extreme close range or long range playstyles. Long range players use scout and pulse rifles for primaries, and sniper rifles for secondaries. Short range players specialize in melee attacks and point-blank shotgun blasts. Players that vary their weapon choice also tend to include melee attacks, and special abilities such as grenades and super abilities. Player preference for PvE or PvP varies between two extremes, and within each game mode preferences for specific activities are revealed through average playtime and specific types of kills.

In addition to the three main dimensions described above, the results also demonstrate variability in features that are either more subtle or secondary to *Destiny*'s main gameplay goals of collecting items and defeating enemies. E.g. the ratio of player resurrections performed to received was significantly above average for some clusters. In these cases, the values for the remaining features did not seem to follow any identifiable pattern. This could mean that some players are inherently more attuned to supportive roles, regardless of their preferences for certain weapon types. Another feature - the average time remaining in a PvP activity when a player quits - allows for inferences to be made about more nuanced player behavior. Some clusters show high values for this feature, suggesting that some players may be more likely to leave early if a match is not going their way.

From the above similarity matrix and clusters, the following conclusion can be drawn: Each method gives varying results compared with the other methods. If one specifically knows what kind of behavior needs to be analyzed, it is crucial that the appropriate method is used during the exercise, e.g. k-means for more general behavior or archetype analysis for more extreme behavior. Otherwise, it is important for a clustering project to include a variety of methods in order to evaluate a wide range of player behaviors, encompassing both general/typical behavior and more extreme behavior.

The developers of *Destiny* have managed to design an apparently well-balanced game when it comes to player performance; a digital experience where players with different preferences can adopt diverging strategies in order to hit the level-cap and to continue enjoying the experience beyond that point. The aforementioned balance is apparent in the cluster analysis results, with very different player styles colliding at the top-levels of the game. For developers, an analysis with similar results would serve as an evaluation of the design intent in delivering an experience that can be enjoyed by a variety of players. The results indicate that there is no best method to examine how players form clusters, but that the choice should be determined by the goal of analysis and include multiple models. In essence, different clustering models are more or less suited for specific circumstances or for providing specific views on the data, which means that the choice of clustering algorithm is important [6].

IX. CONCLUSION AND FUTURE WORK

In this paper behavioral profiles were developed for *Destiny* across four cluster models. The results highlight patterns in the behavior of players in the game across PvP and PvE modes, with a focus on performance and playstyle measures. The challenges of operating with high-dimensional behavioral data and comparing results across cluster models has been described and discussed. Future work aims at building on the profiling results towards the creation of an item recommendation system for *Destiny*. The first step in this process will be extending across the character level range, and generate performance/playstyle clusters as a function of progression, adopting a more dynamic performance view. Secondly, the equipment held by each player can be incorporated into the analysis, providing insights into what weapon choices are preferred by the most skilled players for each playstyle at all levels of in-game progression. With this information, a recommender system for suggesting items to players can be developed. Additional work will also focus on methods such as agglomerative and divisive hierarchical clustering. While the methods used in this paper were selected to cover centroid and extrema-based models that have previously been used in games, there are myriad other methods worth comparing in similar fashion.

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