# Controlling the Crucible: A Novel PvP Recommender Systems Framework for *Destiny*

BLINDED FOR REVIEW


## ABSTRACT

Compared to conventional retail games, today's Massively Multiplayer Online Games (MMOGs) have become progressively more complex and volatile, living in a highly competitive market. Consumable resources in such games are nearly unlimited, making decisions to improve levels of engagement more challenging. Intelligent information filtering methods here can help players make smarter decisions, thereby improving performance, increasing level of engagement, and reducing the likelihood of early departure. In this paper, a novel approach towards building a hybrid content and knowledge based recommender system for player-versus-player (PvP) content in the MMOG *Destiny* is presented. The framework groups the players based on three distinct traced behavioral aspects: base stats, cooldown stats, and weapon playstyle. Different combinations of these profiles are considered to make playstyle recommendations and online evaluations through the social community website Reddit are made to compare the performance of the proposed framework.



## CCS CONCEPTS

**•Computing methodologies → Supervised learning by classification; •Applied computing → Computer games;**

## KEYWORDS

Destiny, profiling, behavior, game analytics, recommender systems, recommendation, MMOG, MMOFPS

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## 1 INTRODUCTION

Massively Multiplayer Online Games (MMOGs) have become increasingly more complex as gaming culture and technology mature. MMOGs are constantly introducing new gameplay features and updates, leading to an environment where players have an immeasurable number of choices about how to play the game. Players across all skill ranges, from casual players to professional eSports athletes, want to know how they can play these games better. In this context, being better can be described by a variety of outcomes that range from improving kill-death ratio in the online first person shooter game *Counter-Strike* to scoring higher damage per second in the freemium multiplayer online battle arena game *League of Legends*. A recommender system built for these types of environments would impact how players think about their gameplay and might allow them to engage more with the games.

These systems are not only good for the players, but for the game developers as well. For persistent online games such as *Destiny* that are constantly updated, commercial success rests on the game's ability to keep a community engaged for long periods of time. Having an accurate recommendation system advising players on how to improve will create more incentive to continue playing, since players know that they have a tangible goal to work towards [11, 21, 23].

In this paper, a multi-profile recommendation framework is introduced to address the unique properties of the gaming domain, specifically for the online multiplayer shooter game *Destiny*. Robust and extremely accurate recommendation systems for MMOGs have not been explored thoroughly previously. Existing systems such as collaborative filtering are not appropriate for this setting, since consideration needs to be given to a variety of different metrics and player preferences. The resulting framework provides flexible recommendations on multiple aspects of the game and has potential commercial applications in eSports.

## 2 RELATED WORK

Due to limited space, the review of current state-of-the-art across behavioral profiling and recommender systems in games will be limited to the key references in the field of Game Analytics, which is the specialized domain of Business Intelligence that specifically focuses on games [17].

Over the past few years, Game Analytics has emerged as a core topic in game design and research, forming a core component of game development today [17]. Behavioral telemetry in major commercial game titles are of large volume, highly varied and typically volatile [3, 6, 25]. This is exemplified by *Destiny*, whose back end telemetry servers host over a thousand features for each player, including a daily summary of their performance in the game [10].


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Developing behavioral profiles in modern game development can be challenging. However, it creates great benefit by forming condensed, actionable views of the behavior of the player base, which can inform design, track problems, assist matchmaking, and identify players groups with specific characteristics [21]. A substantial number of papers have been published on behavioral profiling in games, stemming from roots in Game AI [25] and business intelligence requirements that emerged in the game industry during the early 2000s [7, 17].

Cluster analysis is one of the primary tools available for pattern recognition and has been readily applied across disciplines, seeing heavy adoption in Game Analytics due to the ability to explore data and identifying groups of players with similar behavior, or features driving such behaviors [7, 15]. The majority of previous work on behavioral profiling in games, whether from an AI agent or analytics perspective, is focused on employing specific methods, but comparative analyses were provided by Bauckhage et al. [2] and Drachen et al. [8]. Notably, Drachen et al. [10] developed behavioral profiles for a set of 10,000 players of *Destiny*, focusing on discovering the best performing cluster models for the task of handling high-dimensional behavioral clustering. Working with a set of 4,800 randomly selected players and 41 performance-focused features, four cluster models were applied (k-means, Gaussian mixture models, k-maxoids and Archetype Analysis) to a dataset covering two primary game modes in *Destiny*: Player-versus-Player and Player-versus-Environment. The performance of each model was described, and sets of 4-5 playstyles identified across each model. The authors concluded that Archetype Analysis [5, 8] performs best in terms of developing clearly separated and explainable profiles, the latter forming a key quality criteria in games-based behavioral profiling as argued by Drachen et al. [9].

The first paper to specifically utilize behavioral profiling in commercial game titles was Drachen et al. [9] who worked with Self-Organizing Networks from a 1,365 player sample from *Tomb Raider: Underworld*, documenting how over 95% of the players could be categorized into one of four behavioral profiles. Sifa et al. [22] followed up this work by exploring how behavioral profiles varied as a function of progress in the game. Shim and Srivastava [19] utilized segmentation and description to evaluate player behaviors in *EverQuest II*, whereas Thawonmas and Iizuka [16] generated visualizations of player clusters developed using multi-dimensional scaling for the massively multi-player online game (MMOG) *Shen Zhou Online*. Drachen et al. [7] evaluated the fitness of Simplex Volume Maximization (SIVM) and k-means on on data from the MMOG *Tera: Online* and the online team shooter *Battlefield 2*. Normoyle and Jensen [15] employed Bayesian Clustering on the multi-player shooter game *Battlefield 3* to develop player profiles.

While the state-of-the-art of Game Analytics is advancing rapidly, the topic of applying recommender systems in games remains relatively unexplored. Recommender systems initially saw use in games with the focus on training and assisting game AI and are relatively well explored in games for that purpose [13]. However, research on systems for recommending products or behaviors to users are comparatively rare. The first major academic-based inroads towards using recommender systems Sifa et al. [20] focused on recommendation game titles to players based on the games they had played previously, introducing an Archetype Analysis [5] based recommender system for game recommendation across a 3000+ game dataset from the game distribution platform Steam. Around the same time, Valve, the company behind Steam, introduced a recommender system to their storefront (the two projects being unrelated). The work focused on recommending games, similar to movie recommendations on platforms such as Netflix or app recommendations on the AppStore [4, 12]. Similarly, Anwar et al. [1] used collaborative filtering to suggest games to players via evaluating the opinions of similar players. Notably, the system was evaluated via a live player sample, an approach that is also adopted here.

In addition to recommending which games to play, recommender systems can also be used to recommend behaviors to players during play or which items to buy. The potential was mentioned by Sifa et al. [20] and an industry case study described by Weber [24], whereas this is the first study to realize that in the context of MMOGs. Before moving on to describing the methodology, an overview about *Destiny* is given in the following section.

## 3 DESTINY: AN OPEN WORLD MMOFPS GAME

*Destiny* is a mythic, science-fiction themed online first-person shooter set 700 years in the future. Following the discovery of a mysterious, sentient celestial body named "the Traveler", beings on Earth were given the ability of space travel, as well as superhuman abilities. Players assume the role of "Guardians", superpowered beings who defend the Traveler from alien threats with special abilities and superior gunmanship. To do this, they investigate alien activity in the solar system, as well as train against each other in a controlled environment known as "the Crucible."

*Destiny* is, above all else, a polished online first-person shooter (FPS) which draws heavily from Bungie's earlier *Halo* series. Most of the game revolves around a player-controlled character using several of the thousands of weapons available to kill other players or computer-controlled enemies. However, it also incorporates elements from MMOGs such as *World of Warcraft*, which emphasize a social and cooperative element of gameplay as well as a strong focus on collecting new weapons, armor, and items. Destiny offers both player vs. environment (PVE) and player vs. player (PVP) game modes. PVE game modes allow the player to patrol various planets and attempt solo missions, as well as tackle cooperative missions known as "strikes" and "raids".

As far as the MMO elements of the game, *Destiny* offers players the ability to amass various currencies used to purchase weapons, armor, and items such as ammunition packs. Players may also align themselves with a faction to earn reputation with them and earn specialized, faction-specific gear. One large difference between *Destiny* and other similar games in the genre is the restriction of in-game player interaction. Being exclusive to consoles, *Destiny* only allows players to communicate in-game by using emotes and opt-in voice chat.

Also being a role-playing game (RPG), Destiny offers a wide variety of customization options, starting with character customization. A player may choose to be male or female, one of three races, and one of three classes (Titan, Hunter, and Warlock), each with three subclasses. Each subclass contains a "skill tree" which lets players further customize their character by choosing special abilities and augmenting their agility, armor, and recovery (base stats). Respectively, these stats affect how fast a player's character moves, how durable they are, and how fast they can recover from damage taken.

All PVP gameplay occurs in the Crucible, a training ground where guardians practice their gunmanship before engaging the enemy in combat. Given the highly competitive nature of the Crucible, players are always on the lookout for an advantage over their opponents. Some may seek more powerful weapons and armor, while other may look to change their character's customization via base stats and cooldown stats. Knowing the vast amount of variability in the player base, it's important to consider several aspects of the gameplay when offering a recommendation, rather than honing in on only one or two. A player may not be keen on a recommendation to change his weapon, but would enjoy advice on which stat allocation to choose, or vice versa. The multi-profile recommendation framework that is proposed aims to address this challenge of inherent player preferences in gaming recommendations.

## 4 DATA AND PRE-PROCESSING

The datasets that are generated are based on a random sample of 10,000 players from the available pool of total players. The only requirement was that any given player had to have played the game for more than 2 hours. By taking a random sample of 10,000 players, conclusions can be made about the overall Destiny population, and the biases associated with selecting from a pool of top players are avoided. The final dataset was a combination of two distinct datasets. Both of these datasets were generated through the Bungie API in 2016 and stored as large JSON files. These datasets were pulled during *The Taken King* expansion, released on September 15, 2015. While only a subset of players are used for this paper, it is important to note that *Destiny* passed 30 million active players in 2016 [14], and has been running since 2014, which means that the dataset from the game is of substantial scale by now. Furthermore, it is important to note that any profiles generated in the game are by their nature of limited shelflife as accurate representations of the players, since *Destiny* is constantly patched and updated.

The first of these datasets was tracking 930,000 Crucible (PvP) matches. Each time a player enters a PvP match, Bungie tracks information about that player in addition to any other players in the match. Within PvP matches, Bungie is primarily collecting "performance" data. Performance data gives us information on how the player behaved and what they did during the match. This includes metrics related to their score (such as kills, deaths, assists, total points, etc...) and metrics related to their behavior (such as the amount of kills with a particular gun, which weapons they used, their average time alive per life, etc...). In total, Bungie is tracking 46 metrics for each player in a match. However, since Bungie tracks the players quite extensively, and our analysis is focusing on player behavior and playstyle, we can immediately drop any metric that isn't related to the player's PvP performance (such as the match id, team name, team id and more).

Within a PvP match, a player can get a kill in 15 separate ways (all of the ways are listed in the feature definition). The kills earned with each of the 15 weapons was converted into a proportion. By doing so, the issue of players having different number of matches and number of kills is avoided. Proportions also give us more information about a player's preferred weapon overall. In order for our recommender system to recommend weapons, a player's favorite weapons had to be calculated. The usage of specific weapons per player was aggregated in order to find a given player's overall usage of a particular weapon. After parsing all the matches the aggregated dataset consisted of 8,873 characters and 38 features.

The second dataset was the "main" information about each of the 10,000 players. Here Bungie tracks aggregated information on almost everything related to the player's characters. This includes a player's appearance, gear, level, weapons, and much more. It is important to note that this information was aggregated across the lifetime of a player and this dataset was pulled in early 2016 and updated in mid 2017. As such, this is a "snapshot" of the player's current status at the time the data was pulled. Within this dataset, the most relevant information was in the "base stats" and the "cooldown stats" of the players. A more detailed explanation of what these stats are is included in the feature definitions. Since these stats effect various aspects of combat, a player's distribution of their stats should be reflective of how they play the game. After parsing the dataset, the stats were converted into proportions. This is important due to the varying level of the players. A player with better gear will simply have more raw stats than another player with worse gear, but if both of these players have placed the majority of their stats in a specific category we would like to be able to identify these players as being similar. Taking the proportion allows us to normalize the issue of varying levels and quality of gear (which will give a player more raw stats). After parsing the data, the second dataset consisted of 24,116 characters and 6 features in total.

Given that the goal of this analysis is introducing a recommendation system for players to get better, it is critical to consider the features to recommend against. In other words, we need to select a feature that allows us to determine which players are "good" players. Candidates for this feature are character level, lightlevel, and combat rating.

Character level ranges from 1-40 and players can increase their character level by playing the game more and earning "experience points". As they earn more experience points, their character will continue to level up until they reach the final level, after which they can no longer increase their character level. However, a large problem with the character level is that level 40 is a very easily achievable cap. Players are able to go from level 1-40 simply by playing the game, and there is a large portion of Destiny waiting for players after they have reached level 40.

On the other hand, lightlevel is calculated from a player's equipment stats. In Destiny, better equipment will have more raw stats and as such better equipment will result in higher light level. In order to get better equipment in Destiny, a player has to spend additional time playing the game after reaching level 40. Two level 40 players can have very different lightlevels depending on their respective equipment. It is important to note that getting better equipment takes skill in addition to time (whereas character level can be earned just by playing).

Combat Rating, which is discussed in more detail in the feature explanations, is used as an overall measure of a player's skill. There are a number of metrics available to be used as a measure of skill. However, we believe combat rating makes sense for this analysis. Additionally, since Combat Rating is unique to the PvP mode, it is fitting for our analysis which is focused on the PvP portion of Destiny. As such, we choose to use Combat Rating as the feature to compare player's skill levels and to determine which players were better.

Due to the competitive nature of PvP in *Destiny* and the time taken to acquire gear in *Destiny*, the players that are being recommending against should have played the game long enough to earn their preferred gear. If the entire pool of players is considered, there will be people who are playing with specific gear simply because they have no other choice (and recommending this gear would be problematic since this gear may not be the original player's desired gear). By considering a subset of players that have played the game long enough, it becomes more likely that the player's equipment is the equipment they actually want (since they have had the time to earn gear and select the items they want to use). Since character level is easily attained, and combat rating can be high regardless of playtime (on the *Destiny* leaderboards some of the overall highest combat ratings are associated with players who have played only 50 PvP matches), the decision was made to subset the tracked players based on their "lightlevel".

As discussed above, lightlevel is calculated from a player's equipment and requires time and skill to increase. At the time this data was taken (during the *Taken King Expansion*), the maximum light level attainable in the game was 335. By considering the top 40 percent of players, those with a light level above 200, we ensure that the players in our dataset have enough playtime and have freedom of choice in their equipment. This decision was made since low-level players will not have played the game long enough to have earned their desired gear and often lack choices for their gear (since they have not earned much gear). Taking the top 40 percent increases the likelihood that these players have had the time, and options, to find and select their desired gear.

After merging the two datasets, the initial pool of characters decreased from 24,116 to 8,873. Naturally, since our analysis is focused on PvP, only characters that had appeared in the 930,000 tracked PvP matches were considered. Additionally, since *Destiny* tracks all their players quite extensively, we were able to create a concise subset of the overall data. After merging, the initial subset based on lightlevel, and the initial feature extraction, the final dataset consisted of 2,153 characters and 32 features (from the initial random sample of 10,000 players and 24,116 characters). We list the features we used in our recommender system in the following subsections.

- **Combat Rating:** Combat Rating (CR) is a metric designed by Bungie that is used to assign a single number that is representative of a given player's overall skill. Although the exact calculation of Combat Rating is hidden by Bungie, we know generally how Combat Rating changes. If a player wins a match, their CR will increase. Similarly if a player loses a match, their CR will decrease. Many online games with matchmaking have some variant of an ELO/Ranking system. Combat Rating, like other ELO systems, is quite important for a game's matchmaking system to produce balanced matches where all the players are of similar skill levels.

- **Proportion Base Stats:** Here we are dealing with the proportion of points placed into Agility, Armor, and Recovery. Agility is used to increase a player's overall movement speed and jump. Before we talk about armor and recovery, it is important to talk about how health works in Destiny. A player's overall "lifebar" is split into two segments: actual health and a shield. Every player has the same amount of health and shield regardless of what their stats are. Armor can be thought of as damage reduction *in addition to* a player's base defenses. In other words, when the shields go down, a player with higher armor will lose less actual health per hit relative to a player with lower armor. Recovery, on the other hand, effects how fast shields recharge, and reduces the delay of recharge (the time between a shield going down and starting to "recharge"). Additionally, each character created starts with a bonus to one of these three stats. For example, if a player chooses to be a Hunter, their character receives a +5 bonus to agility.
- **Proportion Cooldown Stats:** Similar to the Base Stats we also consider the proportion of points placed into Discipline, Intellect, and Strength. In PvP matches, there are 3 specific attacks that are on a "charge". In other words, these are attacks that require time to recharge before they can be used again. These three attacks are a character's grenade, super, and melee attacks. Discipline helps grenade attacks recharge faster, Intellect helps super attacks recharge faster, and Strength helps melee attacks recharge faster. We would like to note that proportions were used for the Base and Cooldown stats as a way of normalizing the effect of a player's gear. Players with better gear will have a larger value of raw stats compared to players with worse gear.
- **Inventory List:** To characterize weapon usage, the inventory list is an aggregated list of the weapons used by a player throughout all tracked PvP matches.
- **Kills-Death Ratio:** One of the de facto first person shooter player ranking features is the kill(s)-death(K/D) ratio [7], which is the ratio of a player's total kills to their total deaths in a given match. Higher kills-death ratios are correlated with better players.
- **Average Score Per Life/Per Kill:** These features are the player's average score per life (each time they die) and per kill (their average score at the time of a kill). A player's score is a combination of their kills, assists, and any other in-game actions such as capturing an objective. These features help to distinguish players with similar kills-death ratio. A higher average score per life indicates a larger impact on the game.
- **Resurrection:** Whenever a player dies, there is the option to "revive" the dead player. A living player must interact with the dead player and take time to revive the dead player. If this action is performed successfully, the previously dead player will be alive and able to resume playing in the current match again. If a dead player is not revived, they will have to wait until the match has ended in order to become alive again.
- **Proportion Offensive/Defensive Kills:**
  In the PvP matches, there are specific match types that are objective-based, such as "Control", where players work together to gain control of an objective/area on the map. During these matches, offensive and defensive kills represent the player's kills that haven taken place either capturing or defending the objective.
- **Average Kill Distance:** To consider proximity preferences of users we incorporate the average kill distance as a feature as well. This keeps track of how far the player is from the other players that are killed. Players who prefer long range weapons, such as snipers, will have a much higher average kill distance than players who prefer close range weapons, such as shotguns.
- **Proportion Weapon Kills**
  This composite feature consists of 14 separate features. The proportion of weapon kills represents the proportion of kills that a player got with a specific weapon type. In Destiny, a player has the freedom to change their weapon load-out after each death. As such, the proportion of weapon kills provides reliable information on how a player chooses to play the game. The possible weapons a player can get a kill with are as follows: Auto Rifle, Fusion Rifle, Grenade, Hand Cannon, Machine-gun, Melee, Pulse Rifle, Rocket Launcher, Scout Rifle, Shotgun, Side Arm, Sniper, and Super. The weapons all have varying levels of power, firing rate, and effective distance. In general, there is a balance between these characteristics. Fig. 1 illustrates the distribution of players

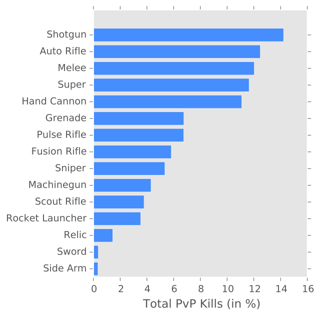



**Figure 1: Distribution of kills (in %) for each weapon type. We can see that auto rifles, hand cannons, melee, shotguns and supers are all fairly popular, with each accounting for about 12 percent of overall kills (and 60 percent in total). The remaining weapons are less popular, with each accounting for about 4-6 percent of overall kills, excluding side arms and swords which account for less than 1 percent of overall kills combined. Notice that the more popular weapons require less accuracy to use compared to the less popular weapons. Low accuracy weapons, such as the shotgun and auto rifle, require less skill to use than high accuracy weapons, such as scout rifles and sniper rifles.**

**Table 1: Profiles based on Base Stats Cluster**

| Cluster | Profile Name | Description |
|---|---|---|
| 1 | Tank | High Armor/Recovery & Low Agility |
| 2 | Speedster | Maxed Agility & Low Armor/Recovery |
| 3 | Bruiser | High Agility/Armor & Low Recovery |
| 4 | Guerrilla | Maxed Recovery & Low Agility/Armor |

killed by the various weapons. This distribution allows us to see weapons that the overall community uses to get kills.

## 5 A PVP RECOMMENDER SYSTEMS FRAMEWORK

The goal was to come up with a novel way to recommend in-game items and stats allocation to Destiny players. Instead of using a single recommender profile, a multi-dimension approach to player profiling was conceptualized and used as a framework for the final recommendation model. The basic tools we used for the profiling based recommender systems framework are based on factorizing given data matrices.

### Player Profiling with $k$-means Clustering

A popular technique to group similar players together in the field of game analytics is $k$-means Clustering. This method was chosen as it provides an efficient way to characterize the different behaviors of players on average. $k$-means clustering groups a given dataset into a certain number of clusters (assume $k$ clusters) fixed a priori. The algorithm focuses on calculating centroids for each of the cluster and assigns each data point to the nearest centroid. This process is done iteratively until the centroids converge to their final values. It results in minimizing in-cluster variance and maximizing inter-cluster variance, which is exactly what was desired when it came to classifying players in Destiny. Traditionally, $k$-means does a good job in classifying average tendencies in the dataset and is not the best approach if trying to find clusters that define extreme behaviors of players. As explained later in the paper, Archetype Analysis was used when it was desired to cluster players based on their game-play styles.

When it came to analyzing the base stats and cooldown stats of players, the extreme allocations would just be maxing out on one of the stats which doesn't help in the classification process. Hence, it made sense to use k-means to come up with the common configurations the players were using for their characters.

Silhouette analysis was used to evaluate the $k$-means clustering results and to select a "reasonable" number of clusters. Silhouette analysis graphically represents the results of any clustering algorithm where each cluster is represented by a

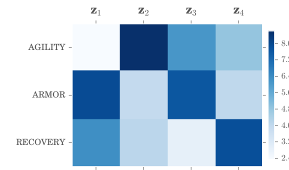



**Figure 2: Results on clustering base stats. The results show two clusters (0 and 2) are high on two base stats and two clusters (1 and 3) are maxed out on one stat, but low in the other stats. Players tend to have a preference for one or two base stats as opposed to equally allocating to all three.**

**Table 2: Profiles based on cooldown stats**

| Cluster | Profile | Description |
|---|---|---|
| 1 | DISC/INT | High on Discipline and Intellect |
| 2 | DISC/STR | High on Discipline and Strength |
| 3 | STR/INT | High on Strength and Intellect |

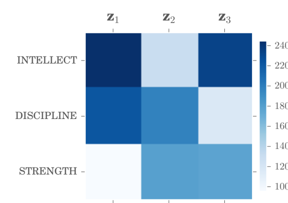



**Figure 3: Different clusters on Cooldown Stats. The results show clusters that are high on two stats and low on the other. Players tend to prefer having very low cooldowns on two abilities instead of equally spreading across all three.**

*silhouette*. The silhouettes represent the distance between clusters and additionally show how well the observations are fitting in each cluster. The silhouette coefficient is calculated using the mean within-cluster and the mean nearest-cluster distance for each sample. The silhouette coefficient falls between -1 and 1, where 1 is the best outcome and -1 is the worst. A silhouette coefficient of 0 implies that the clusters are overlapping, whereas negative values imply observations have been placed in the wrong cluster. All of the profiles were evaluated through silhouette analysis to select an appropriate number of clusters and to evaluate the performance of the clustering algorithms.

*Profiling Base Stats:* The game has three base stats that were focused on namely, Agility, Armor & Recovery. Players customize their characters by allocating points to each of these base stats to complement their class and game-play style. After analyzing the results from $k$-means for 3, 4 and 5 clusters, the 4 cluster results were chosen to be the best balance between granularity and interpretable clusters. The cluster definitions can be visualized using Fig. 2. Using domain knowledge on Destiny and other games, each of the clusters was assigned a profile to reflect the thought process of the players behind their allocations. The 4 profiles created based on base stats are shown in Table 1.

*Profiling Cooldown Stats:* The game also has three other stats that players can allocate to improve the cooldown times of various abilities like special, grenade, etc. These stats could also serve as potential profiling metrics to characterize players and their play-styles. $k$-means clustering was performed over the three cooldown stats, viz. Strength, Discipline & Intellect. In the case of cooldown stats, it made sense to have 3 clusters as more often than not, the players would max out on 2 of the 3 stats based on their requirements. Allocating equally to all 3 is much sub-optimal and is rarely done by the high-level players. The cluster definitions and profile assignments can be seen in Fig. 3 and Table 2 respectively.

### Player Profiling with Archetypal Analysis

In *Destiny*, players are constantly changing their playstyle, whether to try out something new or to keep up with the meta (using the "bestfi gear at a given point in time). As such, we wanted to identify the main playstyles in the game. Archetypal analysis is used to determine the extreme entities, the *archetypes*, in a given dataset. These archetypes are prototypical points that will represent a given population. Once the archetypes have been identified, every player in the dataset can be represented as a convex combination of these extremes.

The archetypes are typically not manifestations of actual players, but rather are manifestations of extreme behavior qualities. Thus, players typically have less extreme values

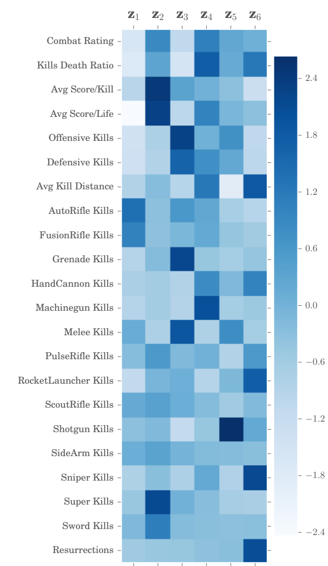



**Figure 4: Illustration of six distinct archetypes of playstyles. Six archetypes were chosen based on the interpretability and distinctiveness of each archetype. Some archetypes are defined by specific weapon usage, such as 1, 5, and 6 for Auto Rifles, Shotguns, and Sniper Rifles respectively. Other archetypes represent a general playstyle, such as 2 being a player who relies on timing their super ability to score massive amounts of points.**

relative to the archetypes. After calculating the archetypes for each of the players in the dataset, players were assigned to the archetype with the largest value, resulting in archetypal clusters. Since Archetypal analysis is focused on the extreme entities, there is a more pronounced difference between the archetypal clusters relative to the difference in centroid based clustering algorithms. The optimal number of archetypes was 6, based on the scree plot and additionally based on the distribution of players falling into each archetype.

### The Recommender System

Rather than relying on a single dimension for building the recommender system, all the three different player profiles across base stats, cooldown stats and in-game performance were used. The recommender approach was two-pronged:

(1) Recommend weapon loadouts to players based on similar players
(2) Recommend optimal allocations for both base stats and cooldown stats

*Weapon Recommendations:* For a given player, the first step was to find similar players using the three profiles, viz. base stats, cooldown stats & playstyles. The 3-way intersection set (region 1 in Fig. 5) of players having same profile assignments as the target player was found. From these set of similar players, we filtered out two players - the best player & the closest (most similar) player.

The best player was found by simply finding the one having the maximum value for combat rating. The closest player on the other hand was found using the k-nearest Neighbors technique. The k-nearest neighbors was fit on all the parameters used in the Archetype Analysis. The system then recommends weapon loadouts for both of these players respectively labeling them as loadouts for best and closest player. *Stats Allocations:* For recommending optimal stats allocation, a different approach was required, as they act as one of the three profiling dimensions. Due to this reason, when computing intersection sets of similar players the dimension to be recommended is left out. For instance, when recommending optimal cooldown stats allocation, the 2-way intersection (region 1 + region 2 in Fig. 5) between base stats and playstyles is computed. Also, as the allocation of stats is closely tied to the class of the character, an additional filtering was added to keep only players belonging to the same class as that of the target player. On top of this, only similar players that had a higher combat rating than the target player were kept. Taking these measures ensured that the recommendations made sense and would be useful to the player.

After finding the desired set of similar players, the distribution of players was calculated on the recommendation dimension. Continuing from the precious example of recommending optimal cooldown stats allocation, the distribution of the similar players was calculated across the three cooldown profiles. The profile containing the maximum number of players was then compared with the target's cooldown profile and an appropriate recommendation to move points across the three stats was provided.

## 6 EVALUATION AND RESULTS

Recommender systems usually evaluated in offline and online fashion[4, 12, 18, 20]. Offline evaluations provide an ability to gauge the accuracy of the algorithm without having to test the system with live users. Instead they utilize existing data with some removed information [12, 20] to *simulate* live systems. The recommender algorithm is evaluated by its ability to recommend the missing information. After applying the recommendation, the difference between the recommended information and the actual information is calculated via a loss function [4, 12, 18].

While usually robust for a wide variety of recommenders, this approach was not appropriate for multi-profile recommendation, as one its main components is weapon information. Weapons in Destiny are, by nature, highly substitutable by other weapons. For example, while one shotgun may be used by a slight majority of top tier players, another shotgun may be just as deadly in the hands of slightly different, but indistinguishable to the algorithm, players. For this reason, calculating loss off of the recommendations would be next to impossible [1, 4, 12, 18, 20]. For this reason, an evaluation via a user study as defined by Shani and Gunawardana [18] was instead performed on real *Destiny* players (a similar general approach also adopted by Anwar et al. [1]).

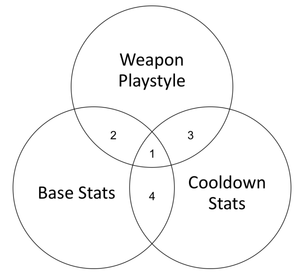



**Figure 5: Illustration of the three different player profile perspectives we use to generate our recommendations. The main idea of the multi-profile recommendation framework is illustrated here. For each of the profiles represented as circles, there are clusters within each profile that a player falls into. Each intersection represents the pool of players that can be considered for recommending on. For example, lets say Player X wanted recommendations on how to improve. Intersection 1 represents players that are most similar to X across all three profiles since they fall into the same cluster/archetype assignments. However, Player X may wish to know how players similar to him across two profiles, but different in the third, are doing. Intersections 2,3,4 represent players that are different in a third profile. For example, taking the players at intersection 2 to recommend on would give show players that are varied in cooldown stats. This recommendation framework provides a flexible way to consider different aspects of gameplay and take into account what the player is willing to change.**

**Table 3: Summary Statistics of Reddit User Sample**

| Measure | Mean | Max | Min |
|---|---|---|---|
| Time Played (Hours) | 112.4 | 122.1 | 106.2 |
| Light Level | 384.7 | 400 | 209 |
| Combat Rating | 94.9 | 144.4 | 52.4 |
| Kills+Assists/Death Ratio | 1.2 | 2.1 | .1 |

### User Study Evaluation

To evaluate the potential of the recommender, general sentiment and opinion was sought from the active users on Reddit community /r/DestinyTheGame. This community was chosen due to its strong engagement with the game and penchant for all things related to *Destiny*. Naturally, taking a sample of players from this community will contain inherent

Base Stats:

| Profile Name | Description |
|---|---|
| Tank | High Armor/Recovery, low Agility |
| Speedster | Maxed Agility, lower Armor/Recovery |
| Bruiser | High Agility/Armor, low Recovery |
| Guerilla | Maxed Recovery, lower Agility/Armor |

Your player is a **Tank**.

**Figure 6: Section 1 of the personalized player report. Players are given descriptions of each cluster within each profile, and told which cluster their character falls into.**

**This is the best player's most common loadout:**
**Primary:** Haakon's Hatchet, Auto Rifle
**Special:** Strongbow-D, Shotgun
**Heavy:** Gjallarhorn, Rocket Launcher
**Combat Rating:** 134.45

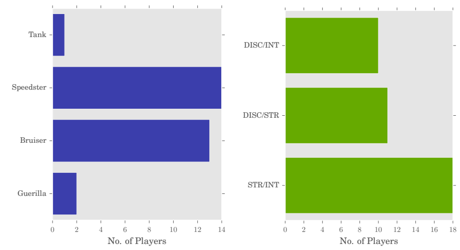
**This is the loadout of the player MOST similar to you (your nearest neighbor):**
**Primary:** Harrowed Smite of Merain, Pulse Rifle
**Special:** Queenbreakers' Bow, Fusion Rifle
**Heavy:** Harrowed Elulim's Frenzy, Rocket Launcher
**Combat Rating:**105.03

**Figure 7: Section 2 of the personalized player report. Players are told the top weapon loadout of the best player in their intersection, by combat rating, as well as the top weapon loadout of their nearest neighbor.**

bias. Most active users on the community have been playing since the game's release and follow the metagame (a continually evolving strategy which gives players competitive advantage) quite closely. The benefit of asking such a community to evaluate the recommender is the experience that comes with the users. Each user has extensive experience with the game and was able to provide educated feedback about the performance of the system. The drawback of using the reddit community, however, is that the sample of users surveyed is biased. The users were already enthusiastic about *Destiny*, and may have responded more positively than a randomly selected sample. See Table 3 for sample statistics.

*Destiny* player data was collected from the reddit sample and personalized recommendations were generated for each user. Contents of the reports included four sections:

(1) **Profile Assignments** - Describe each profile (base stat, cooldown attribute, playstyle) and tell the user which cluster they fall into under each profile.
(2) **Weapons** - Give the user the top weapon loadout (Primary, Special, and Heavy Weapon) for the best player, as well as the top weapon loadout for the user's nearest neighbor.




**(a) Base Stats Profiles** **(b) Cool Down Stats Profiles**

**Figure 8: Section 3 of the personalized player report. Given a user's base stat and cooldown stat allocations, the distribution of how other similar, but better, players allocate their stats is shown.**

(3) **Stats** - Show the user how players with higher combat ratings allocate their stats. Two histograms are shown visualizing the distributions of players in two sets of profiles, one for base stats, and the other for cooldown attributes.
(4) **Recommendation** Based on the weapon usage of players better than the user, up to three suggested weapons are shown as recommendations, as well as a suggestion on how to reallocate stats (if necessary). Average combat rating of the players using the recommended weapons and stat allocations is shown to reinforce the validity of the recommendation.

Reports were sent to each user with a survey attached, asking several questions about their opinion of the usefulness of the recommendation and whether or not they would act on the recommendation. It is important to note that the metagame of Destiny changes from update to update, so there's no way a recommendation based on year old data would be seriously considered by top players. This is why players were asked to evaluation the recommendation under the mindset that the results were still relevant in today's metagame.

Out of 50 users, 30 responded to the survey with overwhelmingly positive sentiment. When asked "Did you find the recommendation report helpful?" and "Would you act on the suggestion in order to see if your gameplay would improve?", over 80% of respondents responded positively. When asked "Would you like to see this implemented into a website for you to use?", over 90% said yes. Given the nature of the recommendations, the positive response is encouraging for the potential of the algorithm. With real-time data and willing users, proper recommendations could be provided for players to the end of improving their in-game performance.

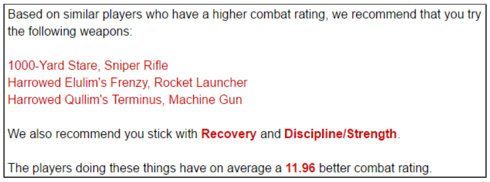



**Figure 9: Section 4 of the personalized player report. A final soft recommendation is delivered based on the current stat allocation and weapon choice of the user's character. Validation of the recommendation is given by telling the user that players who have made these choices have a better combat rating.**

## 7 CONCLUSION AND FUTURE WORK

In this paper, a multi-profile recommendation framework was developed for *Destiny* across three distinct game play features: base stats, cool down stats, and weapon play style. This framework allows for flexibility in choosing which features to recommend on and how much variability is desired for those features. An online evaluation of the system through Reddit revealed the recommendations were interesting and valuable to players. Furthermore, players revealed that they would act on these recommendations in order to see if their gameplay would improve. Future work regarding this system involves longitudinal live testing on the recommendation framework, meaning select players would be followed and game telemetry would be analyzed to see if these players improved from the recommendations they were given.

While three profiles were chosen here, the methodology is designed to be generalizable to $n$ number of profiles. Doing this would create numerous distinct intersections to build the recommendation on, encompassing any desired complexity of any game. To use another game as an example, perhaps a four profile-system could be built for a *League of Legends* player where the profiles are item build, mastery trees, rune pages, and ability leveling. This has significant implications in the eSports scene, an environment where even the smallest advantages lead to winning competitive matches.

## REFERENCES


[1] S. M. Anwar, T. Shahzad, Z. Sattar, R. Khan, and M. Majid. 2017. A game recommender system using collaborative filtering (GAMBIT). In *IEEE Applied Science and Technologies.*

[2] Christian Bauckhage, Anders Drachen, and Rafet Sifa. 2015. Clustering game behavior data. *IEEE Transactions on Computational Intelligence and AI in Games* 7, 3 (2015), 266–278.

[3] J. Bohannon. 2010. Game-miners Grapple with Massive Data. *Science* 330, 6000 (2010), 30–31.

[4] Koren Y. Turrin-R. Cremonesi, P. 2010. Performance of Recommender Algorithms on Top-N Recommendation Tasks. In *Proceedings of ACM Recommender Systems Conference.*

[5] A. Cutler and L. Breiman. 1994. Archetypal Analysis. *Technometrics* 36, 4 (1994), 338–347.

[6] Anders Drachen, Eric Lunquist, Yungyen Kung, Pranav Rao, Diego Klabjan, Rafet Sifa, and Julian Runge. 2016. Rapid Prediction of Player Retention in Free-to-Play Mobile Games. In *Proc. of AAAI AIIDE.*

[7] A. Drachen, R. Sifa, C. Bauckhage, and C. Thurau. 2012. Guns, Swords and Data: Clustering of Player Behavior in Computer Games in the Wild. In *Proc. of IEEE CIG.*

[8] A. Drachen, C. Thurau, Sifa R., and Bauckhage C. 2013. A Comparison of Methods for Player Clustering via Behavioral Telemetry. In *Proc. of FDG.*

[9] A. Drachen, G. N. Yannakakis, A. Canossa, and J. Togelius. 2009. Player Modeling using Self-Organization in Tomb Raider: Underworld. In *Proc of IEEE CIG.*

[10] J.and Gray-C.and Harik E.and Lu P.and Sifa R.and Klabjan D. Drachen, A.and Green. 2016. Guns and guardians: Comparative cluster analysis and behavioral profiling in destiny. In *Proceedings of IEEE Computational Intelligence in Games.*

[11] El-Nasr, M.S. and Drachen, A. and Canossa, A. 2013. *Game Analytics: Maximizing the Value of Player Data.* Springer.

[12] Rokach L. Ricci-F. Shapira B. Kantor, P. 2011. *Recommender Systems Handbook.* Springer.

[13] B. Medler. 2011. Using Recommendation Systems to Adapt Gameplay. In *Discovering in Gaming and Computer-Mediated Simulations: New Interdisciplinary Applications.*

[14] M. Minotti. 2016. Destiny passes 30 million registered players. https://venturebeat.com/2016/05/05/destiny-now-has-over-30-million-registered-players/, *VentureBeat* (2016).

[15] A. Normoyle and S. T. Jensen. 2015. Bayesian Clustering of Player Styles for Multiplayer Games. In *Proc. of AAAI AIIDE.*

[16] J.-K. Lou R. Thawonmas, K. Yoshida and K.-T. Chen. 2011. HAnalysis of revisitations in online games. *Entertainment Computing* 2 (2011), 215–221. Issue 4.

[17] Magy Seif El-Nasr, Anders Drachen, and Alessandro Canossa. 2013. *Game Analytics - Maximizing the Value of Player Data.* Springer.

[18] Guy Shani and Asela Gunawardana. 2009. A Survey of Accuracy Evaluation Metrics of Recommendation Tasks. In *Journal of Machine Learning Research.*

[19] K. Shim and J. Srivastava. 2010. Behavioral Profiles of Character Types in EverQuest II. In *Proceedings of IEEE Computational Intelligence in Games Conference.*

[20] R. Sifa, C. Bauckhage, and A. Drachen. 2014. Archetypal Game Recommender Systems. *Proc. of KDML-LWA* (2014).

[21] R. Sifa, A. Drachen, and C. Bauckhage. 2017. *Profiling in Games: Understanding Behavior from Telemetry.*

[22] R. Sifa, A. Drachen, C. Bauckhage, C. Thurau, and A. Canossa. 2013. Behavior Evolution in Tomb Raider Underworld. In *Proc. of IEEE CIG.*

[23] R. Sifa, S. Srikanth, A. Drachen, C. Ojeda, and C. Bauckhage. 2016. Predicting Retention in Sandbox Games with Tensor Factorization-based Representation Learning. In *Proc. of IEEE CIG.*

[24] B. Weber. 2015. Building a Recommendation System for EverQuest Landmarks Marketplace. *Game Developers Conference* (2015).

[25] G. Yannakakis. 2012. Game AI Revisited. In *Proc. of ACM Computing Frontiers Conference.* 285–292.