Machine Learning for Pinnacle Matchmaking in *Destiny 2*

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***Abstract*—Video games often contain online components that allow players across the world to interact and play with one another. The systems which perform the matching of players into teams are often collectively referred to as "matchmaking." We focus on analyzing matchmaking in the video game *Destiny 2*, an online first-person shooter developed by Bungie. In this paper, we develop and apply machine learning techniques to Destiny 2 game data exposed by the Bungie.net Platform API, with the goal of predicting the "success" of the matching of a group of player, as measured by end of game standing and time to activity completion. The main contributions of this paper are (1) a structured data pipeline for retrieving, processing and aggregating data scraped from the Platform API, (2) data analysis and application of machine learning for supervised and unsupervised tasks, and (3) explorations of and proposals for future work in feature engineering.**

***Index Terms*—Category: Finance and Commerce, video games, matchmaking, regression, data collection, API**

I. Introduction and Problem Motivation

In the realm of online gaming, *Destiny 2* is unique in that it facilitates player interaction in many ways. Players can organically encounter each other online while exploring the game's many worlds, as well as prompt to get matched with other players in order to participate in cooperative and competitive activities. This latter process, a more explicit form of matchmaking, depends on the fact that there are other players currently online who are looking to play the same activity. However, there are some activities that have matchmaking disabled, due to the difficulty, coordination, and prerequisites required for the activity (these activities are referred to as "pinnacle" or "aspirational" activities—the things you do to demonstrate mastery over the game).

This design choice has created an ecosystem around finding people to play with, and there are already several established networks that exist for finding teammates, such as LFG ("looking for group") websites, and clans, organized groups of players that regularly play together. Bungie themselves have an in-game matchmaking solution, called Guided Games, which attempts to pair solo players (Seekers) and organized teams (Guides). Unfortunately, Guided Games has been in beta since the game's original release in 2017 [1], and it suffers from low concurrent player populations and, by extension, long queue times [2]. The advantage of clan membership (and, to some extent, using LFG apps) are that players can schedule activities in advance, but these routes can be intimidating to new or introverted players. One potential approach that could improve the experience of looking for a team would be to use a system to recommend other players they could play an activity with right now, or in the near future: a "team-activity-time" recommendation. Instead of putting the onus on a player to find a group, the system can take advantage of the fact that many people are in similar situations, wanting to play the same activity—and proactively match them.

As a step towards that goal, we employ a number of machine learning techniques on data publicly accessible via the Bungie.net Platform API [3], with the goal of evaluating the success or fitness of a matched group of players. This system could be employed in a matchmaking pipeline to make recommendations on which players could play an activity together.

More formally, we define our task as a supervised learning task, where the examples are historical games whose information we can query from the API, and the labels are measures of "success" reported by the game—for example, the time it takes to complete an activity, or the team's standing, victory or defeat, at the end of a game.

The paper is structured as follows: In section II, we outline a process for scraping data from the *Destiny 2* API. In section III, we outline the methods we tried for learning on our task. In section IV, we detail the experiments we tried and evaluate the results of our exploration. In section V, we situate our work and results in the existing literature. In section VI, we summarize our results and discuss avenues for future work.

II. Data Collection

Collecting data was a significant component of the project due to the nature of its source. Traditional datasets with well-formed features are not publicly available for *Destiny 2*; however, some data is exposed via the Bungie.net Platform API, opening the door for scraping together a dataset. The API contains upwards of 100 endpoints that allow both first-party and third-party apps to access and manipulate various in-game and player data.

This project was done for CS229: Machine Learning. The code is available on GitHub at garrickf/d2-ml. Thanks to Prof. Moses Charikar, Prof. Chris Ré, and the rest of the teaching team for their feedback on the project and a great class!

Of these many endpoints, only a subset provide any useful information for our learning task. For example, the `Destiny2.GetPostGameCarnageReport` endpoint returns a summary of information related with a given `activityId`, internally referred to as a post-game carnage report (PGCR). The `activityId` is an unsigned 64-bit integer, and it is assigned to activities in ascending order. See Fig. 1 for an example PGCR response.


```
{
    "Response": {
        "period": "2021-05-07T10:06:12Z",
        "startingPhaseIndex": 0,
        "activityDetails": {
            "referenceId": 1575864965,
            "directorActivityHash": ...,
            "instanceId": "8400554258",
            "mode": 63,
            "modes": [
                64,
                63
            ],
            "isPrivate": false,
            "membershipType": 3
        },
        ...
    }
}
```


Fig. 1. Truncated JSON PGCR response (full length is 2844 lines) for `activityId = 8400554258`. This is a game of Gambit (a competitive player vs. player mode, with additional non-player combatants (the "environment"), often categorized as PvPvE. There are additional fields for player statistics and game metadata.

Assuming we rate-limit our requests to 25 per-second (the limit imposed by the API), querying activity information for every `activityId` from September 2017 to the present (about 8.4 billion activities) would take upwards of 10 years! To make things feasible, we limit our range to a period of 10K/100K activities performed starting at an arbitrary `activityId` (we picked one for a game played around May). We implemented a threadpool to parallelize outgoing requests, rate-limiting to avoid throttling; this sped up data collection by up to fourteen fold.

An additional layer of complication in the data collection is the presence of hashes in the response rather than localized English strings (see See Fig. 1, `directorActivityHash`). The API is internationalized, and so the API responses are decoupled from any language, and an additional hydration step is needed to transform hashes into localized English strings. In particular, a manifest (a file containing metadata for a group of accompanying files—in our case, all the data we can query from the platform API) can be downloaded as a compressed SQLite database. The tables therein map hashes to localized strings, representing static definitions of objects found within *Destiny*.

We wrote an additional script script to download the manifest and process it into an index used in the data collection routine.

There is a level of stochasticity in the web scraper, as some requests time out, network issues arise, etc. In addition, our scraper does not reattempt a query for a failed `activityId`; as such, on one particular run of scraping 10K activities, we got back 8789 instances and 6042 scraped attributes (many empty), spanning 124 unique activities (see Table I). The distribution of activities are shown in Fig. 2, Fig. 3, and Fig. 4.

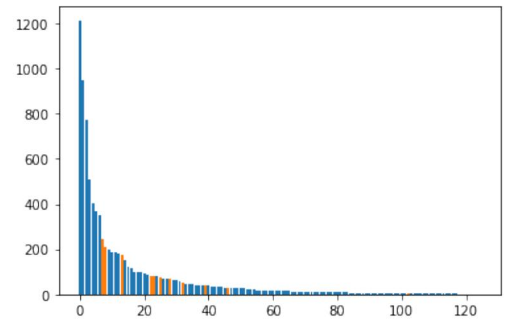

Fig. 2. Distribution of activity type from 10K queries (field name: `directorActivityHash`); the activities players choose to play follows a power distribution. Activities from Fig. 4 are highlighted in orange for comparison.

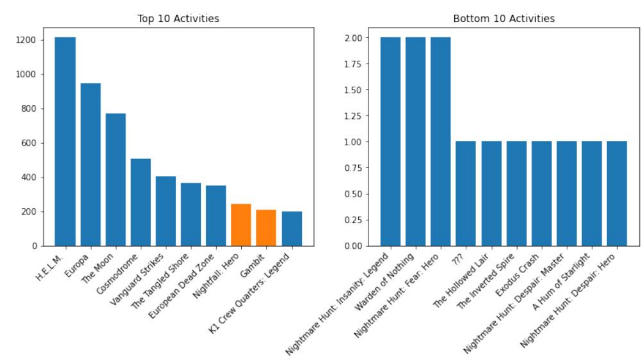

Fig. 3. Distributions of the top 10 and bottom 10 activities. Popular activities are social spaces ("H.E.L.M.") , free roam ("Europa," "The Moon," etc.), possibly because they act as hubs or places to visit before other, more challenging activities. Activities from Fig. 4 are highlighted in orange for comparison.

TABLE I
DATA COLLECTION RESULTS

Scrape	Examples Found	Attributes Found	File Size
10K	8789	6042	55MB
10K (Gambit)	223	114	150KB
100K	80026	11498	0.93GB

We configured the scraper to filter data by game mode, as each game mode supports a different number of players and exposes different metadata and stats (in Gambit, for example, players seek to defeat an enemy boss, the Primeval, that isn't present in other game modes, and thus carries unique statistics). This has the added benefit of reducing the number of "empty" columns.

We focus our attention on the game mode Gambit. Due to its requirement for team cooperation, Gambit matches are a good source of statistics for how teams behave and work together. From our initial 10K scrape, we filtered out 223 Gambit matches, with 113 attributes per example. The relatively high number of attributes is due to collecting statistics for each player, and there are eight players minimum per Gambit match (sometimes, a player may leave the match, in which case an additional player joins to fill the team).

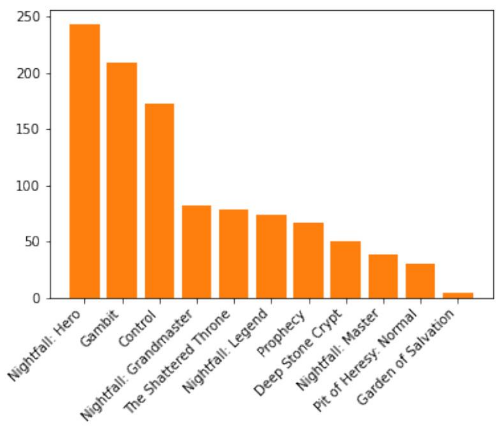

Fig. 4. Distribution of activities selected by the author. Aside from the top three, all activities here do not have matchmaking by default, so recommendations would be most impactful for these pinnacle activities. Game modes like Gambit or Control can also serve as a good proxy, because of their competitive nature.

III. Methods

There are multiple factors of "success" in a single *Destiny 2* game or match. If the game mode does not contain opposing teams (player vs. environment, or PvE), the activity completion time can be taken as a metric of team cohesion and success. The longer the time to completion, the worse the team did. In competitive game modes (PvP or PvPvE), there are separate competing teams, and the standing, or end-of-game result (victory or defeat) can be taken as a metric of team success.

In order to learn and predict completion time, we consider several methods. One method is linear regression, whose cost function is given by:

$$J(\theta) = \frac{1}{2}\sum_{i=1}^{n}(h_\theta(x^{(i)}) - y^{(i)})^2 \tag{1}$$

where $h_\theta(x) = \sum_{i=0}^{d}\theta_i x_i = \theta^\top x$ (we use the convention of letting $x_0 = 1$, the intercept). This function is convex. We can derive this cost function from a probabilistic/MLE perspective. The vectorized update rule for batch gradient descent is

$$\theta := \theta + \alpha\sum_{i=1}^{n}(y^{(i)} - h_\theta(x^{(i)}))x^{(i)} \tag{2}$$

Notice we don't normalize over the number of examples (as is convention with neural networks). Also note that the negative sign typical in gradient descent (we move against the direction of the gradient to minimize the cost function) has been pushed inside the sum in (2).

As there are a lot of features, and some of them may be collinear (for example, the number of kills versus the number of combatants defeated, i.e., kills and assists), regularization may result in better, simpler models and less overfitting to the training data. We consider ridge regression and lasso regression, whose cost functions are least squares with L2 and L1 regularization, respectively. The cost function for Ridge regression is:

$$J(\theta) = \frac{1}{2}\sum_{i=1}^{n}(h_\theta(x^{(i)}) - y^{(i)})^2 + \lambda\|\theta\|_2 \tag{3}$$

Where λ is the regularization strength. The cost function for Lasso regression is:

$$J(\theta) = \frac{1}{2}\sum_{i=1}^{n}(h_\theta(x^{(i)}) - y^{(i)})^2 + \gamma\|\theta\|_1 \tag{4}$$

Where γ is the regularization strength. By taking a Bayesian interpretation of regularization, we can view ridge and lasso regression as having a Gaussian and Laplace prior over the parameters θ, respectively. Both priors encourage the parameter values to be closer to their mean (i.e., zero), resulting in a shrinkage effect. In particular, lasso regression is known to result in sparse parameters, where most parameter values are zero, and only some are non-zero. This could be useful for identifying which features are the most useful for our learning task.

To evaluate the methods above, we use the coefficient of determination R^2, which is defined as:

$$1 - \frac{u}{v} \tag{5}$$

Where u is the sum of squared residuals over our validation (or test) set:

$$u = \sum_{i=1}^{n_{\text{val}}}(y^{(i)} - \hat{y}^{(i)})^2 \tag{6}$$

and v is the total sum of squares, defined as:

$$v = \sum_{i=1}^{n_{\text{val}}}(y^{(i)} - \bar{y})^2 \tag{7}$$

where in 7, $\hat{y}$ is the mean of the observed data. Intuitively, this statistic gives some measure of the goodness of fit for our model. The best possible R^2 score is 1.0.

IV. Experiments, Results and Interpretation

A. Tools

In developing our data collection pipeline described in section II, we used Postman [4] in order to inspect and explore the results of API calls. The requests library was used in order to make the calls.

We used an external library, scikit-learn [5], to perform the methods described in Section III. Numpy and pandas were used for data manipulation, and matplotlib was used for making visualizations.

B. Regression on Activity Completion Time

See Table II for a collection of the results. We reduced the number of features down to 81 by removing duplicate features (e.g., each player had an activity completion time, but they were all the same). We try both normalizing features and leaving them unnormalized. As there are different scales of features (for example, the kills a player performs in a match, versus points they earn, which may be on a different scale), we would expect normalization of features to help here.

For ridge and lasso regression, we additionally performed hyperparameter search over the regularization strength.

It appeared lasso regression with normalized features and moderate regularization strength ($\gamma = 1$) outperformed other models on the validation set. Notably, if the regularization strength was tuned too high, this resulted in a poor fit to the data, even reaching 0.0 with $\gamma = 10$ (this indicates a constant model that disregards the input features).

Inspecting the parameters returned by the model, we find that only 13 of the 81 features are selected, and they are primarily the number of player deaths for each of the characters. Ranked by importance, we see that number of deaths is a primary factor in determining the length of a Gambit match (see Fig. 5).

TABLE II
REGRESSION ON ACTIVITY COMPLETION TIME

Method	Reg. Strength	Train R^2	Val R^2	Test R^2
LinReg	N/A[a]	**0.8299**	0.6944	
LinReg*	N/A	0.8268	0.6803	
Ridge	0.03	0.8297	0.6934	
	0.1	0.8293	0.6925	
	0.3	0.8285	0.6930	
	1	0.8276	0.6962	
	3	0.8266	0.6991	
	10	0.8252	0.6978	
Ridge*	0.03	0.8252	0.6959	
	0.1	0.8208	0.7115	
	0.3	0.8091	0.7265	
	1	0.7749	0.7371	
	3	0.6984	0.7136	
	10	0.5081	0.5568	
Lasso	0.03	0.8290	0.6935	
	0.1	0.8264	0.6966	
	0.3	0.8255	0.6937	
	1	0.8211	0.6859	
	3	0.8116	0.6418	
	10	0.7885	0.5899	
Lasso*	0.03	0.8224	0.6817	
	0.1	0.8153	0.6745	
	0.3	0.7959	0.7135	
	1	0.7253	**0.7667**	0.6463
	3	0.4121	0.4442	
	10	0.0000	-0.0348	

[a]Regularization applies only to Ridge and Lasso.
*Indicates normalization of features was applied.

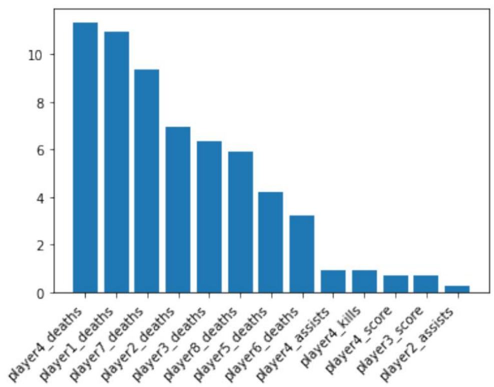

Fig. 5. Non-zero weights and attributes selected by the best lasso model, as evaluated using Table II. Deaths are weighted more than other features.

Why could this be? It turns out, there is a mechanic in Gambit called "Death Heals Primeval," where player deaths can cause the final boss to regenerate health. This would likely have a direct impact on the length of the match, as players would have to spend more time defeating the boss with each additional death they incur.

V. Related Work

This project seeks to look at ways of performing machine learning on scraped video game data in order to facilitate better matchmaking, whether between currently online players, or as a "recommendation" system for all players, online and offline, in a game's pool. The TrueMatch system, developed by Minka and Zaykov at Microsoft Research [6], has the similar goal of using AI for matchmaking. Their system uses a reinforcement learning model in order to build a probabilistic model of the matchmaking process that can predict increases in online player populations and adjust tolerances for network latency and skill gap in order to reduce waiting times for players. Skill iteslf may be measured by another system; Herbrich, Minka, and Graepel outline an ELO-like system called TrueSkill [7], a Bayesian skill rating algorithm based on approximate message passing in factor graphs.

In contrast, our project is from the perspective of not having access to internal data, or aggregated data over a player's history (such as skill or ELO rankings). As such, the learning task is somewhat harder, and there are less "good" quality features to work with. In light of *Destiny*'s unique pinnacle activities requiring player coordination and having matchmaking disabled, we care much more about team skill and fitness. We also note that in the use case of offline recommendations, factors like ping (internet connection) may not be as important as they would be in an online matchmaking process, which TrueMatch seeks to optimize.

Other analyses of *Destiny* data have been done; Bouchet has analyzed the frequency of player activities as a function of light level (a type of level that grows with in-game experience) [8], and some websites have more thoroughly scraped PGCRs to produce their own ELO rankings of players, much like TrueSkill [9].

VI. Conclusion and Future Work

In conclusion, we outline a method for data collection on the *Destiny 2* API, giving us access to statistics on games and players that we can attempt to learn information from. This data was then applied to the task of determining player and team success in activities—in particular, we took a closer look at activity completion times in the competitive game mode Gambit as a proxy for team success. The main challenges were in scraping the data from the API, interpreting them as features, and reducing the dimensionality of the data by dropping or aggregating features.

While we found that deaths are bad for a team in Gambit, this may not be the case in other activities. There are hundreds of activities in *Destiny 2*, each of which demand different skillsets and forms of communication. More analysis needs to be done for other game modes in order to make a better judgement.

For future work, we would be interested in performing feature engineering to produce more aggregate features. This could involve combinations of existing features, or additional scraping of the API to get more data. For example, an approximation of player ELO scores could be obtained by querying for a player's activity history (`Destiny2.GetActivityHistory`), and computing the number of wins, number of kills, types of activities played, etc. In addition, the system which scrapes data from the API could be made more robust (retrying failed requests, caching data, etc.).

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