# Statistical Analysis of Player Behavior in Minecraft

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## ABSTRACT

Interactive Virtual Worlds offer new individual and social experiences in a huge variety of artificial realities. They also have enormous potential for the study of how people interact, and how societies function and evolve. Systematic collection and analysis of in-play behavioral data will be invaluable for enhancing player experiences, facilitating effective administration, and unlocking the scientific potential of online societies. This paper details the development of a framework to collect player data in Minecraft. We present a complete solution which can be deployed on Minecraft servers to send collected data to a centralized server for visualization and analysis by researchers, players, and server administrators. Using the framework, we collected and analyzed over 14 person-days of active gameplay. We built a classification tool to identify high-level player behaviors from observations of their moment-by-moment game actions. Heat map visualizations highlighting spatial behavior can be used by players and server administrators to evaluate game experiences. Our data collection and analysis framework offers the opportunity to understand how individual behavior, environmental factors, and social systems interact through large-scale observational studies of virtual worlds.

## Categories and Subject Descriptors

I.3.7 [**Computer Graphics**]: Virtual Reality; I.2.1 [**Artificial Intelligence**]: Applications and Expert Systems—*Games*

## Keywords

Virtual world, game, Minecraft, player data, game analytics, telemetry, online societies

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## 1. INTRODUCTION

Interactive Virtual Worlds (`IVW`'s) have a huge potential for scientific research. The new challenges and datasets they offer have earned virtual worlds a large and growing place in game analytics. Their lack of constraints relative to other game types allows for the study of game features that promote creativity, which in turn makes them a natural setting for developing the educational potential of games. Their collaborative nature makes them an excellent domain for extensions of game analytics in social directions. Such social analytics include simple tools for monitoring summary statistics about social networks, player teams, or game chat, up to more ambitious metrics that may ultimately be able to quantify the cohesiveness of a collaborative community. Complementary to monitoring of social activity is the development of game features or mechanics that can actually promote teamwork and collaboration. Finally, interactive virtual worlds have unique potential to advance the social sciences. Not only do they make experiments cheap and practical, in many cases virtual worlds make society-scale experiments, for the first time in history, possible. Even without experimental control, there is vast potential in the datasets that can be created by passively recording game behavior. Being digital, virtual worlds can provide unprecedented access to the complete state of a social system — down to the most minute data — at arbitrarily fine-grained resolutions of time. Such data is particularly valuable in the relatively constrained environment of a game, in which we know that players have goals and are motivated to solve them. These features remove much of the stigma of artificiality that afflicts laboratory experiments. While one may argue that digital-game behavior is, by definition, not real-world behavior, scholars like Castronova [5, 7] cast doubt on the existence of a fine line, and emphasize that the value of games can be cast in more orthodox terms, even those of "true" economic value.

Whether from the viewpoint of user experience or computational efficiency, statistical analysis of player behavior is important to the development of large virtual worlds. Within Minecraft user forums, players and administrators often express a desire to create particular types of experiences. Analyzing the types of experiences players actually have in play is the first step in achieving their goals. Furthermore, predicting where players will move within the environment, and

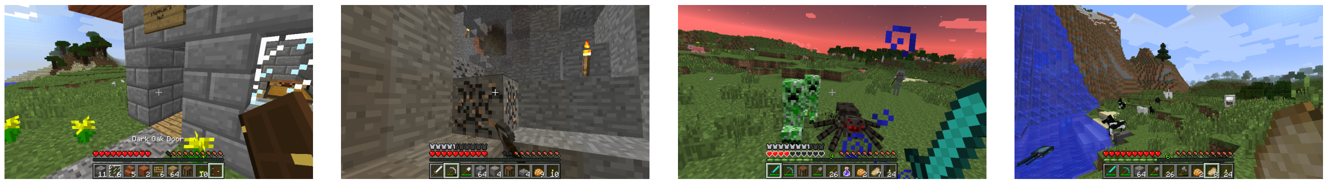


**Figure 1: Typical player behaviors found in Minecraft**

what actions they will perform, may allow for a more efficient use of computational resources [13], and enable larger, more interesting worlds.

Minecraft is very well-suited for the collection of social game analytics, and well-position to benefit from them. With well over 50 million sold copies, it has a large user base and a very active community. In its basic form, the game is an open world "sandbox" with no obvious goals. The nature of the game motivates players to explore, mine for resources, and build infrastructure. As soon as multiple people start playing on the same server, communities and even economies start to emerge. The game can be modified with custom code that enables players to introduce new game mechanisms or craft immersive experiences for others. It is possible to build any kind of virtual world, in-game or programatically.

This paper presents a framework for analyzing player behavior in interactive virtual worlds. We explore different ways of acquiring data, and introduce a suite of Minecraft server plugins that facilitate the collection of high-resolution, high-quality player behavior data. These include: (1) data collection of arbitrary in-game events from any participating server, (2) unobtrusive system to query users for their subjective or qualitative impressions, and (3) systems for managing virtual worlds to run social experiments. We demonstrate the application of our framework on several use cases, including the classification of player behavior, the extraction of descriptive statistics, and the real-time production of visualizations. Our classifier provides a particularly thorough showcase of the power and flexibility of our framework: it was built on fine-granularity data collected by one plugin, and trained on subjective ground-truth data collected by another. This paper makes the following main contributions.

1. An open-source data collection and analysis framework for capturing player behavior in Minecraft
2. Information visualization tools to help serve meaningful information to researchers, players, and server administrators.
3. A validated classifier of player activities into categories based on Bartle's character theory [3].

As well as providing data for academics in social science, computer science, and education, our tools also have great potential to help players, server administrators, and the communities they constitute. Information about the relative contributions of different players can help in the identification of key community members. Visualizations and other information about a world can also help administrators identify troublesome activity and diagnose problems in their worlds.

### 1.1 HeapCraft

The framework introduced in this paper is part of the HeapCraft project which aims to explore the scientific potential of Minecraft. More information, tools and source code can be found on `http://heapcraft.net/`.

## 2. RELATED WORK

As in every facet of digital game research, the major impediment to progress in our understanding of interactive virtual worlds is that most datasets are proprietary and held closely by their owners. Consequently, most analyses of game behavior are probably being conducted in the private sector in service of corporate missions. Unfortunately, their results are usually kept secret. While data is traditionally collected from playtesters in special user experience labs, the recent Destiny Public Beta[1] has dramatically increased the amount of collected data by allowing anyone to become a playtester. Player data in online games may continue to be analyzed long after a game's official release [6].

Researchers have shown that virtual worlds give us an unprecedented ability to implement controlled experiments at the scale of whole societies [6, 2]. Virtual labs make it easy to reach large numbers of people across sociocultural boundaries and perform large-scale, long-term experiments. While, most game research is cast in terms of its relevance to games, and less in terms of its relevance to social science, the fundamental similarities between interactive virtual worlds and online social networking sites suggest that the former should be considered at least as valuable as the latter for advancing our understanding of social-scale processes generally [1, 18, 19, 4, 12, 9]. Economists have used transaction data from online multiplayer games to study trading behavior [8] and have shown the potential application of virtual worlds to study macro-scale phenomena empirically, even within studies that lack experimental control [7]. Ducheneaut and Yee [11] present player data that they collected with a framework for analyzing World of Warcraft. They used client plugins to log data about players, the game publisher (Blizzard Community API), as well as surveys. Since online games often attract young players, game research in virtual worlds may be particularly valuable for research about the development of sociality, creativity, and even morality in children. At present, the child-oriented research on games that is not focused on education tends to

[1]`http://destiny.wikia.com/wiki/Destiny_Public_Beta`

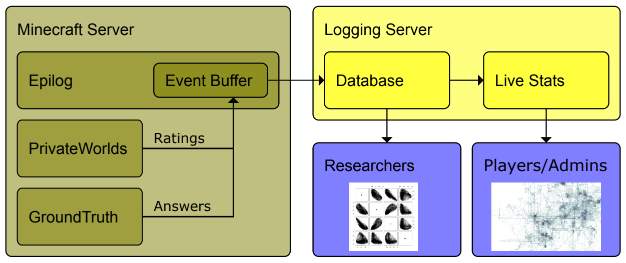


**Figure 2: The framework we used to collect player data. Plugins installed on a Minecraft server collect player events and send them to a logging server. Researchers can access the raw event data. Players and administrators are able to access preprocessed and aggregated live statistics.**

focus on the direct effects of a given game or type of game on children [24, 25, 20].

Player modeling [26] is a critical element to providing personalized game experiences, and is a prerequisite towards achieving adaptive gameplay [14]. For example, direct sensor measurements may be used to modify the behavior of virtual agents in interactive virtual environments [21]. PaSSAGE [23] establishes the importance of player modeling in interactive storytelling by introducing player-specific stories using automatically generated events.

## 3. FRAMEWORK

Our framework consists of the interacting components illustrated in Fig. 2. The Epilog plugin records player actions and sends them to a central logging server. The other plugins use Epilog to send additional data to our database. Our logging server can collect data from multiple Minecraft servers simultaneously. This is valuable because, unlike other multiplayer online games, Minecraft is predominantly served by players, rather than by its developers. Minecraft administrators opt-in to sending us their data by installing the Epilog plugin on their servers.

While others have pursued client-side data collection options, we chose to pursue a server-side solution. This allows us to collect data from many different players by only having to collaborate with the server administrator. Logging all players at once allows us to record all changes made to a virtual world, to compare players' behaviors within the same environment, and to capture all player interactions. On the other hand, logging by modified clients would make it easier to study individual players across multiple servers. But the available data would be limited to the immediate surroundings of players using the modified clients.

The plugins are written using Bukkit[2], an unofficial Minecraft server API whose server, CraftBukkit is popular for its heavy modifiability. As it stands, our software is not compatible with the official server binaries, or with other unofficial projects that are not Bukkit-compatible. The Bukkit project received a DMCA takedown request on September 3rd, 2014. It remains to be seen how this development will influence adoption of the very popular CraftBukkit server relative to other variants.

[2]`http://bukkit.org/`

### 3.1 The Epilog Plugin

Epilog collects user-generated events and sends them to our logging server every 10 seconds. By default, it records all player-related events provided by the Bukkit API, but additional events can easily be added. In addition to the event name, time, player, server address, and world ID, event-specific attributes like item names and block positions can be added as desired.

We logged an average of about 12 events per second for an active player. Move events were the most frequent; walking generates 20 position updates per second (though some activities generate over 50 events per second).

Plugins are able to detect if the Epilog plugin is installed and can use it to send their own data to our logging server. The PrivateWorlds plugin uses this feature to log when a player rates a map or creates a new instance of a map.

### 3.2 Ground Truth Plugin

We also created a plugin that sends player messages over the in-game chat system at random intervals. We used the plugin to collect subjective "ground truth" data for our player classifier by asking the players what they are doing. i.e., if they are building, exploring, fighting, or mining.

### 3.3 The PrivateWorlds Plugin

We developed the PrivateWorlds plugin to allow us to run virtual laboratory experiments, or analyze maps played in single-player mode. PrivateWorlds allows players to instantiate their own copy of a prepared map. The plugin creates a new player state for each map. Items or abilities can not be transferred between worlds. The result is like having many private servers, or like playing Minecraft maps offline.

The user interface is a combination of console command and virtual in-game buttons. A player can teleport to an automatically generated PrivateWorlds "hub" world at any time by typing `/pw`. Inside the hub the player can choose one of the provided maps by pressing a virtual button. To leave the map, `/pw` can be typed again.

In order to collect user feedback, additional rooms can be built inside the hub. On our server, we teleport the player into a room with buttons with which they can rate their experience upon leaving a map. The plugin can easily be extended to allow random assignment to worlds that differ in accordance with experimentally-controlled parameters.

### 3.4 Public Access to Descriptive Statistics

To help our tools serve the Minecraft player community, we built a website containing information about the project and our server. The website features live statistics fetched from recorded data, like the total play time and the number of diamonds mined. We plot data in a way that can preserve player privacy and anonymity. For example, we included a live heatmap of player positions since launch, but this map

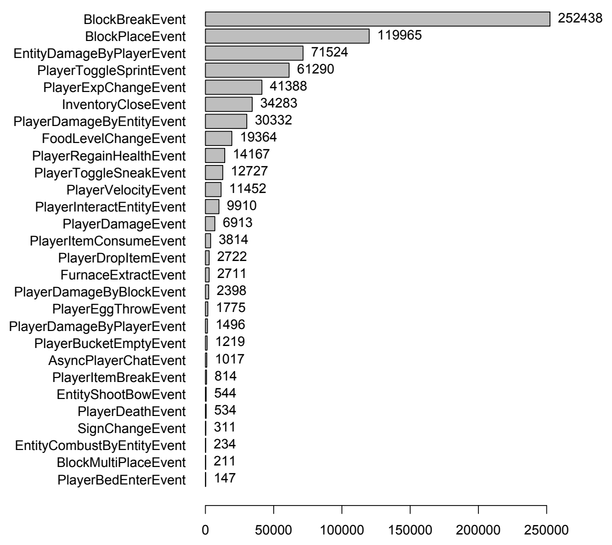


**Figure 3: Number of recorded events during 62 days of player collection, with over 14 person-days of active gameplay.**

is focused on only a subset of the world to permit players to build without scrutiny. On the other hand, server administrators have access to a complete heatmap for observing overall player activity and discovering emerging hotspots.

## 4. DATASET

In order to get a first dataset for statistical evaluation, we set up our own Minecraft server. Having the logging plugin installed from the beginning allowed us to get a complete log of all changes to the initial, randomly generated world. The server difficulty was set to easy and we disabled the ability of mobs to modify the world (e.g. exploding "Creepers" would not create craters in the terrain). Other than that, the server used the default configuration.

We collected player data over a duration of two months, constituting 14 person-days worth of active gameplay. A total of 45 players were active on our server during this time with 30 players active for more than an hour. We did not collect any demographical information, but due to our advertisement, we assume that many of those players were university students. Players who produced less than one hour of activity were not included in the analysis. Fig. 3 shows the number of events included in our dataset. Not shown are 12,644,303 instances of `PlayerMoveEvent`. We also excluded events occurring less than 100 times, events with a very strong correlation to another event (e.g. `InventoryOpenEvent` and `InventoryCloseEvent`), events that did not contribute to our analysis (e.g. `PlayerAnimationEvent` for animating the swinging of a player's arms), and those that were redundant (e.g. `PlayerLoginEvent`).

During this time, we also advertised the plugin to server administrators, and collected about 5 hours of data from servers besides our own. The challenges of attracting server administrators include building awareness, building adoption, and all of the labor — in code development, administration, and community relations — that come with managing free software projects.

## 5. ANALYSIS AND VISUALIZATION

### 5.1 Heat Maps

Heat maps are an excellent tool for visualizing spatial information. In Minecraft, knowing the spatial distribution of player activities can lead to deep insights about the behavior of players, and to more specific insights about the qualities of a particular map. They can help one recognize patterns and locate interesting points.

Fig. 4a shows where players spent their time on the server. Every pixel represents the area of one block. Darker colors mean more time. Houses reveal themselves as dark clouds of movement activity. Underground bases feature more distinct edges. Mine shafts are usually represented by straight, dark lines. The light, random paths usually indicate exploring on the surface. Only a limited area around the spawn point is shown because including the whole active area would obscure details. We ignored players idle for more than 1 second to avoid the hot spots that arise when players leave their keyboards, as when they are waiting for daytime in-game or for their virtual plants to grow.

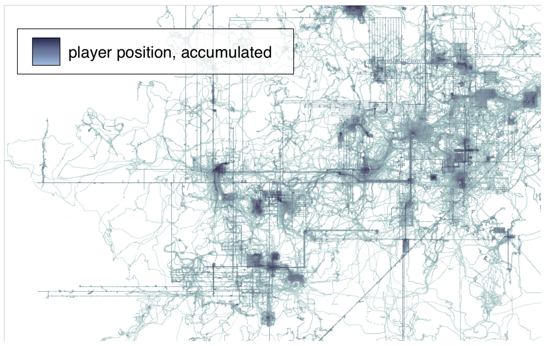
The data used for heat map visualization was scaled using a factor: $\text{sgn}(M) \cdot \log(\text{abs}(M) \cdot a + 1)$ to make the resulting images more readable. $M$ represents the two dimensional data matrix, $a$ is a scaling factor used to enhance image contrast, similar to gamma correction. The function maps real numbers to a scale between -1 and 1. The result is similar to using a logarithmic scale, but works for both negative and positive values.

### 5.2 Quantifying Effort

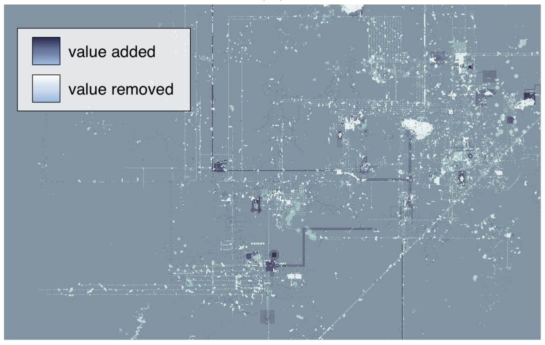
To move beyond the established use of heatmaps for visualizing player traces, we graphed the spatial distribution of economic value as a result of player activity (Fig. 4b). In these plots the effects of Minecraft's eponymous activity are immediately apparent: the game ultimately consists of removing value from some locations (brightness) and concentrating it elsewhere (darkness). Buildings can be recognized as dark rectangles. They get darker by being either tall or made of expensive materials. Mines and farms leave bright traces that result from the removal of blocks and the harvesting of plants. Paths with intermittent dark spots indicate caves lighted with torches.

To calculate the economic values of removed and placed blocks, we consulted blocksandgold.[3] They use a trading system based on a virtual currency to determine the value of items. The price list gets updated daily. We took the values from October 6th 2014. Players on our server are likely to value blocks differently, but data from a different world's economy is expected to give a satisfactory approximation to that in our own. Measures and visualizations of economic value have potential applications in the maintenance and measure of collaborative (or any) activity, and may form the

[3]`http://www.blocksandgold.com/en/minecraft-item-id-price-list/`



(a)



(b)

**Figure 4: Heat maps of player position (a) and block value (b) on our server. Block values are summed over the vertical axis.**

foundation for micro- or macroeconomic analyses of activity in this interactive virtual world.

### 5.3 Game Level Analysis

Our framework can be used to diagnose problems in level or game design. We created heat maps with behavioral data from custom game level maps. The two maps in Fig. 5 show player positions accumulated over time, overlaid with accumulated player deaths (red). The maps are created by recording player data from the map Periculum.[4] and A Light in the Dark[5] respectively. Both maps were played by eight different people.

Difficult parts on the map can be identified by dark colors (players spending a lot of time at the same spot) and by red pixels (players have died). This data can be used to identify areas where the map is too confusing or difficult. Heat maps of this kind can be utilized to distribute the difficulty of a custom map more evenly, so players stay challenged without being frustrated.

## 6. PLAYER CLASSIFICATION

To obtain a higher-level representation of player behaviors and experiences, it is necessary to translate between the moment-by-moment game events such as `PlayerMoveEvent` to states with more abstracted behavioral meanings. Inspired by the scheme of the popular Bartle test [3] we sought to identify behaviors based on Bartle's proposed player types. We used terms that are unambiguous and easy for players to understand: `explore`, `mine`, `build`, and `fight` (an option for `other` was also provided). Training on ground-truth data from player queries, we built a classifier to assign players to these high-level types from patterns in the elementary behavior events they generated.

[4]`http://www.minecraftmaps.com/adventure-maps/periculum`
[5]`http://www.minecraftmaps.com/parkour-maps/a-light-in-the-dark`

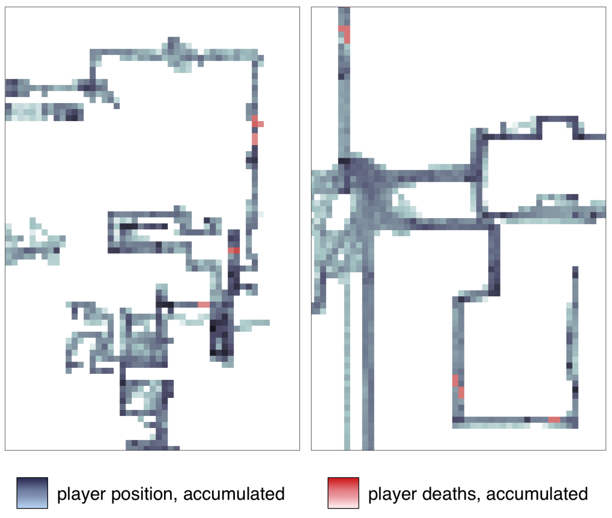


**Figure 5: Heat maps (extract) of player positions and deaths for the maps "Periculum" (left) and "A Light in the Dark" (right)**

### 6.1 Ground Truth Collection

We used our Ground Truth plugin to ask people, at random intervals, what they were doing via in-game chat. The sampling method was inspired by the work of Csikszentmihalyi [10]. The reminder message "`$PLAYERNAME, what are you doing? type /do help`" was sent to players every 3–13 minutes. The "`/do help`" command provides more information about how to use the command. With the `/do` command, players can also make unsolicited reports on their current activities, or, alternatively, turn the (potentially distracting) queries off and back on.

Players selected the behavior they were engaged in by using the first letter, e.g. "`/do b`" for building. We issued 2193 reminders and received 708 self-classifications: 286, 117, 35, 182 and 88 for `build`, `explore`, `fight`, `mine`, and `other` events, respectively.

### 6.2 Features

We pre-processed low-level events into usable features for classification. We ended up using 29 features, listed in Fig. 7a. `PlayerMoveEvent` was transformed into `moveDistance` and the toggle events for sneak and sprint were transformed to time spent sneaking and moving. The other events were represented by simply counting their occurrences.

The classifier used accumulated data within a sliding two-minute window. Accumulating data over a longer period

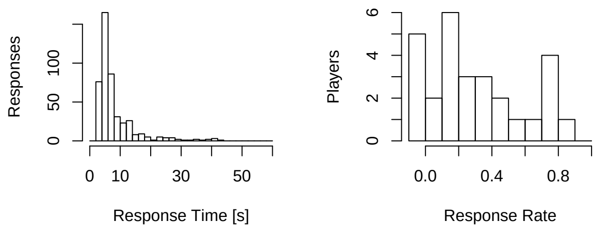


**Figure 6: Response times and response rate of our ground truth collection**

would have had the advantage of capturing a more average view of the behavior. On the other hand, shorter periods would have reduced the risk of capturing several different overlapping behaviors. Specific game tasks usually take well over two minutes, but the time-scale we selected was of the same order as players' responses to our ground truth queries (see Fig. 6). We were unable to significantly improve the accuracy of the classifier by increasing or decreasing the length of the time window. We created the training set by centering each window around the time that a player entered their report for their current activity. Neither moving the center nor weighting the significance of events by distance to the center improved the classification.

After looking at how long it took players to report their activity after receiving the reminder (see Fig. 6), we decided to consider a response as valid if it occurred within 60 seconds of the query. This led to an average response rate of 0.289. The histogram in Fig. 6 on the right shows that five players ignored all the requests, but most players responded to at least some of them. One player deactivated the reminders temporarily and two players permanently. 75 reports couldn't be associated with a request, and seem to have been entered unsolicited. Their temporal distribution was random enough to merit inclusion in our ground truth dataset.

## 6.3 Classification

Using the ground truth data, we built a classifier to summarize from logged data a player's behavior at a given moment. Only data from our own server was used, excluding gameplay inside custom maps. The main dataset contains 11,040 data points generated by slicing the recorded data into two minute windows.[6] The training set contains 620 data points, ignoring the activity `other`.

$V_i(x)$ maps a data point to its aggregated feature value described in section 6.2 where $x \in \mathcal{X}$ is a data point and $i$ is one of the 29 features. $v_i(x) = a_i \cdot (V_i(x) - b_i)$ produces a normalized value where $a_i$ and $b_i$ are chosen to satisfy $\mathrm{E}[v_i] = 0$ and $\mathrm{Var}[v_i] = 1$ for every feature in the main data set. The normalized values describe the deviation from average gameplay and allow us to compare the different features.

[6]Even though we ignored windows without activity, the dataset contains more idle time than our previous play time measurement, resulting in 15.3 days of data.

Classification associates patterns of features in the training data with the behaviors reported by the players. A weight matrix $W_{ij}$ is calculated by first summing up all data points for a certain behavior in the training set. Each row of this matrix $w_{ij}$ is subsequently normalized to unit length:

$$\begin{aligned} W_{ij} &= \sum_{x \in \mathrm{X}(j)} v_i(x) \\ w_{ij} &= \frac{W_{ij}}{\sqrt{\sum_j W_{ij}^2}}, \end{aligned} \tag{1}$$

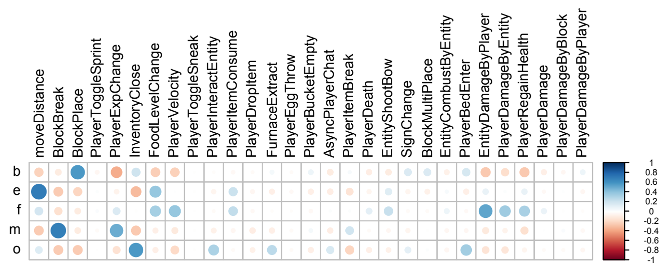
where $\mathrm{X}(j)$ produces all data points with the reported behavior $j$. The resulting row vectors describe the average distribution of features for each behavior, shown in Fig. 7a. Inspection shows that the results make sense intuitively: features one would associate with a certain behavior stand out reasonably well. Principal components analysis (PCA) shows that five components can explain $\tilde{5}0\%$ of the variation in our dataset (Fig. 8b), implying that identifying five high-level behaviors is a reasonable goal, but one that may leave some variation unexplained. The principal components show similarities to our theory-led behavioral groups, for example PC1 is almost identical to “”fighting”, and PC2 has strong similarities to “mining” (noting that components can be sign reversed without loss of generality).

PCA identifies orthogonal components in the data. We did not impose this restriction on our classifier, since we expect there to be overlaps in behavior. Fighting, for example, seems to occur disproportionally often during exploring, resulting in a clearly noticeable fighting component inside the exploring vector. Simultaneously, the number of reported “fight” behaviors was much lower than other behavior types. This needn't imply that our server was particularly peaceful. Fights often don't last as long as behaviors from the other categories, and players might have been too busy to use the console during a fight. They also may already have returned to their previous task when answering or even noticing a reminder. We did not try to separate the variables any further because we wanted to minimize manual tweaking of our data, and any losses of generalizability and reproducibility.

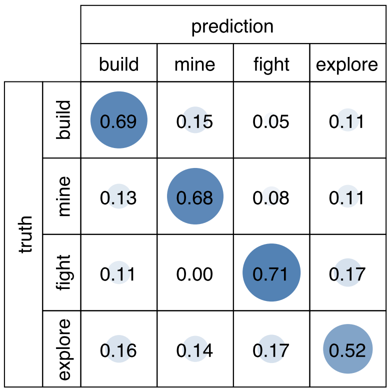
Our linear classifier uses the weight matrix defined above to assign four scores $\mathbf{S}$ to any new input vector $\mathbf{x}$ via the scalar product

$$S_i = \sum_j w_{ij} x_j. \tag{2}$$

The $i$th element of $S$ indicates how closely the window of actions matches the training weights for behavior $i$. The classifier thus predicts that the observed window exhibits a behavior of $\mathrm{argmax}_i S_i$, i.e. the maximal element of $S$. Another way of looking at the classifier is as correlation receiver. The rows of the classification matrix represent matched filters. Since this is a widely-used linear system and its behavior is well-understood, the results are easy to interpret. Actual gameplay usually features combinations of the different actions. If we leave out the last step selecting the maximum, we get ratios for each filter individually, basically transforming the time window into a behavior space. In some cases those additional details might be valuable. Not having competing classifiers also offers greater freedom when adding additional filters.



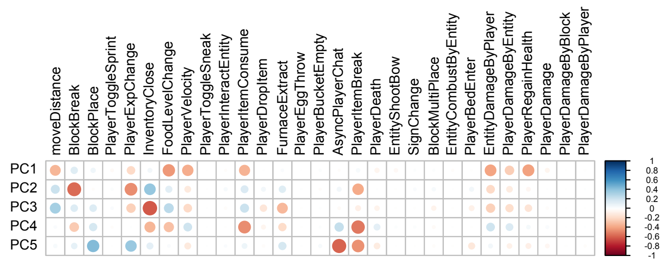
**(a)**



| | | prediction | | | |
|---|---|---|---|---|---|
| | | build | mine | fight | explore |
| truth | build | 0.69 | 0.15 | 0.05 | 0.11 |
| | mine | 0.13 | 0.68 | 0.08 | 0.11 |
| | fight | 0.11 | 0.00 | 0.71 | 0.17 |
| | explore | 0.16 | 0.14 | 0.17 | 0.52 |

**(b)**

**Figure 7: Classifier training and validation, showing the trained weight matrix (a) and confusion matrix from the cross-validation (b)**



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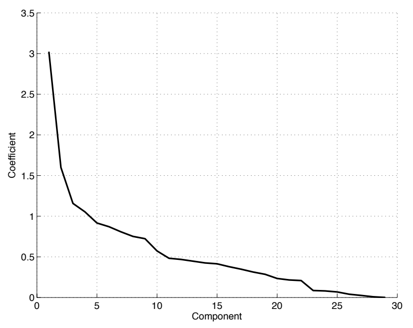

**(b)**

**Figure 8: PCA analysis, showing the weight matrix for the first five components (a) and the coefficient value of each component (b)**

We verified our classifier by using leave-one-out cross-validation. Each sample in our training set was classified using all other samples. The results of the cross-validation are shown in Table 7b in the form of a confusion matrix. The classifier had an overall success quotient of $401/620 = 0.65$. This is 2.6 times greater than a random classification success of 0.25, but several issues could still be limiting the performance of the classifier. A player declaring `explore` could have been mining during most of the measured two minutes. Building a house inside a mountain could (and possibly should) be measured as mining. Before trying to improve the classifier based on the available data, we recommend further analyzing gameplay that leads to misclassifications, e.g. by observing players in play.

**Observations.** Our classification of player behavior uses a combination of linear filters over players' actions within a recorded window of time. Future studies, with potentially larger sets of training data, could investigate whether nonlinear classification (e.g. support vector machines, neural networks etc.) can achieve a more accurate detection of different behaviors.

Most of our classifier's errors were made while attempting to distinguish between exploring and fighting behavior. This could have resulted from the nature of the game or the data collection method: players fight for relatively shorter periods of time, amidst other types of behavior, and are unlikely to be able to report their behavior at the time. Adaptive time-windowing and post-hoc questioning could ameliorate this issue. For example, players could be shown replays of notable action phases (sets of actions differing from the surrounding period) and asked what behavior was being displayed. Distinguishing between different fighting styles might also improve the classifiers accuracy. Fighting with bow and arrow triggers different events compared to sword fights. Fighting on the surface, which includes more movement over greater distances than fighting in caves, is often classified as exploring.

## 7. DISCUSSION AND FUTURE WORK

We successfully built a framework for recording gameplay on Minecraft servers. From one server, our own, we recorded two weeks of fine-granularity player behavior data. The collected data provided interesting insights into players' behavior that can be used to help players, server administrators, and academics. By creating heat maps we were able to recognize different kinds of player activity, and map the extraction and creation of valuable resources in the game. Our classifier allowed us to distinguish between building, fighting, mining and exploring with about 65% accuracy.

The Epilog plugin is likely to be of value to other researchers. Some modifications would certainly improve that value, like the ability to track items that players are keeping in their inventories, putting in chests, or, in the case of arrows, firing at each other.

The method we used to classify players over time could be extended to distinguish between players displaying different behavior in general. Combined with more data from different servers, correlations between server policies, plugins, communities, player types, and player satisfaction are very likely. Our investigation of the online community of server administrators and players suggests that many of them desire to host or participate in worlds where players preferentially exhibit certain behaviors. Automated detection and presentation of player behavior can be used to advertise worlds based on these characteristics, and to allow server administrators to determine whether their hosted worlds meet the specifications they desire. Feedback systems could utilize this analysis to advise server administrators or make in-play suggestions that guide users toward the types of experiences they prefer. Moreover, automated filtering of basic actions into defined behaviors will help identify how world characteristics influence the types of behavior exhibited, creating the opportunity for large-scale observational studies of the efficacy of different rules or mechanisms for producing pro-social collaborative behavior. The PrivateWorlds plugin lets players rate maps after playing them. This information, combined with all the recorded gameplay, can be used to analyze different maps. With such insights, it may be possible to develop algorithms for rating maps automatically.

Our study of player behavior and cooperation in Minecraft is complementary to research in computer graphics and digital storytelling that explores the automated synthesis of player and NPC interactions [16, 22] for interactive storytelling [15, 17]. An interesting avenue of future exploration is to analyse and guide unstructured player experiences in Minecraft towards telling compelling interactive narratives.

Finally, with Minecraft as a laboratory, researchers can expose virtual economies, property systems, and governance institutions to experimental analysis. Many investigations into the development of societies are limited by the relatively small number of different real societies we can study. Systematic analysis of virtual worlds has the potential to overcome this barrier, expanding the number of alternative societies by orders of magnitude. We will continue our efforts to expand our dataset by adding more servers. The plugins, a list of participating servers to play on and more can be found at `http://heapcraft.net/`. The data will be used to analyze player collaboration and will be made available to researchers upon request.[7]

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