HeapCraft: Interactive Data Exploration and Visualization Tools for Understanding and Influencing Player Behavior in Minecraft

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Building Mining Fighting Exploring

Figure 1: *One HeapCraft tool, the Classify plugin, is used to automatically classify the behavior of a player in real-time in Minecraft.*

Abstract

We present *HeapCraft*: an open-source suite of interactive data exploration and visualization tools that allows researchers, server administrators and game designers to analyze and potentially influence player behavior in Minecraft. Our framework includes a telemetry system, several tools for visualizing and representing the collected data, and tools for modifying the game experience in controlled ways. Measures that we use to quantify and visualize player behavior and collaboration have been derived from a large data set containing 3451 player-hours from 908 players and 43 different servers. *HeapCraft* has been demonstrated on a variety of tasks including player behavior classification, as well as quantifying and improving collaboration of players on Minecraft servers. *HeapCraft* is freely available and serves to democratize game analytics for the Minecraft community at large.

CR Categories: I.3.3 [Computer Graphics]: Virtual Reality—[I.2.1]: Artificial Intelligence—Applications and Expert Systems[Games]

Keywords: Social Tools, Virtual world, Game, Minecraft, Player Data, Game Analytics, Telemetry

1 Introduction

Though it is traditionally the domain of game studios, game analytics is as important to players and other people, like game server administrators who volunteer their time to organize and support communities of players. Game analytic tools that can effectively serve this less conventional audience will necessarily have different requirements. While game studios focus on commercial questions, administrators of shared virtual worlds are more likely to be interested in building strong communities among small numbers of players. A possible measure to identify strong communities is player collaboration. By providing feedback and tools for behavioral testing, game analytic tools can make it easier to measure, predict, and improve collaboration in a small community of gamers. Player needs also impose special requirements on a game analytic framework. Players are interested in optimizing their gameplay experience, a goal that can be served with better tools for identification of healthy communities, for inspecting the characteristics of teammates, and for collaborating with other players. A further requirement for player- and community-oriented analytics is sensitivity to privacy issues. Adoption of optional analytical tools by player communities is likely to be resisted if players feel they don't have control over their information. Consequently, any such tools must offer players and administrators transparency about data collection and the ability to control their privacy.

Three components are necessary to make analytical tools that suit the needs of these different types of data users: visualization tools that help analyze and understand player behavior, a large data set of player activities for producing useful metrics, and tools for influencing players towards socially-productive behaviors. In this paper, we present *HeapCraft*: a suite of freely available, open-source data exploration and visualization tools for Minecraft that address the challenges discussed above. They range from simple descriptive statistics to sophisticated measures of collaboration, including tools for: (1) data collection of arbitrary in-game events from any participating server, (2) real-time player behavior classification, (3) measuring player collaboration, and (4) helping players themselves behave more collaboratively.

HeapCraft has been demonstrated on several use cases, including providing real-time feedback to players on their activity and the activity of other active players [Müller et al. 2015b], information visualization tools for server administrators to get a holistic understanding of player activity on their servers, and novel ways of forming communities on Minecraft servers [Müller et al. 2015a]. *HeapCraft* is freely available for server administrators and players to use and serves to democratize game analytics for the Minecraft community at large.

2 Related Work

One of the major impediments to progress in our understanding of interactive virtual worlds is the lack of publicly accessible datasets, and data acquisition and exploration tools. 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.

We have focused our interest on Minecraft because of it's unique potential to reverse this trend. Most Minecraft servers are hosted and maintained not by the game's ownership, but by players. This difference is important because in Minecraft, the population that is most likely to benefit from telemetry and analytics is not the game's ownership, but players who administer game servers and maintain player communities. So, while there is no shortage of impressive work on analyzing game user behavior [Kim et al. 2008; Medler et al. 2011], almost none has addressed the challenges or potential inherent in adapting a game analytic framework for use cases in which the game's community of players is the main consumer of data insights [Canossa et al. 2014]. Minecraft itself is attracting increased interest as research platform, but most interest to-date is from educational and media technology researchers [Leavitt 2013; Schifter and Cipollone 2013; Bukvic et al. 2014; French et al. 2014; Garrelts 2014].

In addition to serving player communities, our framework can also advance science, through the unique potential of virtual world's to permit fine-grained analysis of the Internet's emergent social systems at full scale [Bainbridge 2007; Castronova et al. 2013]. Research on virtual worlds like Minecraft may be particularly valuable for research about the development of reasoning and social skills in young people [Villani 2001; Wollslager 2009; Olson 2010].

3 HeapCraft Tools

HeapCraft encompasses a range of tools that serve both Minecraft players and administrators: The *Epilog Dashboard* for real-time visualizations and analytics of player behavior, *Map Miner* targeted at server administrators for inspecting player positions in a Minecraft world, *Classify* that can quickly code live player behavior into game-relevant classes, *Graph Miner* for data exploration and analysis to study player relationships, and *DiviningRod* which is a Minecraft plugin targeted at improving collaboration. All these social tools are based on data collected by *Epilog* that records all player-related game events, including player movement, block placement, mining and inventory content, and sends it to our server [Müller et al. 2015b]. In total, the dataset contains 3451 player-hours from 908 players and 43 different servers.[1]

3.1 Epilog Dashboard

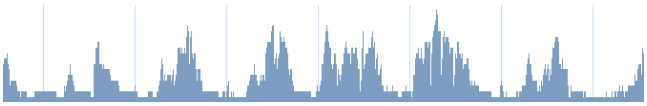
The Epilog Dashboard is a web-based visual analytics front-end which provides Minecraft server administrators with real-time summary statistics of a very wide range of behavioral data. Server administrators have access to various statistics about player activity (see Figure 2). This includes simple count data, such as the number of placed blocks by each player, a player's total travel distance, as well as a number of time-dependent statistics such as the total time a player was active, the last time the player was active and a player's collaboration index (as defined in [Müller et al. 2015a]). The graphic shown in Figure 3 (b) shows the number of online players on a server for the last 7 days. Players can use this information to decide when to play. Heatmaps showing the aggregated player positions in real time, as shown in Figure 3 (c), are particularly popular with server administrators. Hotspots and new settlements can easily be recognized, even if they are underground. Mine shafts manifest as straight lines.

[1] A large part of the dataset will be publicly available for researchers.

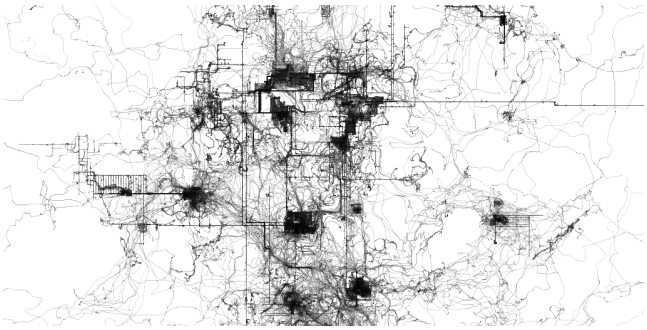
Most Active Players — all players

Name	Last active	Active for	Traveled	Mined	Placed	Social
[redacted]	209d 22h	1d 16h	139,052	27,595	7,446	0.037
[redacted]	182d 9h	1d 12h	211,851	41,762	15,857	0.035
[redacted]	228d 4h	1d 0h	191,096	18,696	12,701	0.093
[redacted]	84d 20h	23h 41m	186,811	15,448	7,349	0.304
[redacted]	134d 23h	22h 3m	217,126	11,140	5,558	0.193
[redacted]	232d 2h	16h 27m	93,127	13,926	9,882	0.057
[redacted]	164d 22h	16h 25m	123,052	10,267	6,246	0.333
[redacted]	228d 3h	16h 4m	109,793	8,816	5,794	0.138
[redacted]	231d 1h	16h 3m	100,770	11,200	7,117	0.170
[redacted]	161d 23h	15h 46m	101,716	9,369	5,222	0.401

(a) Player statistics.



(b) 7-day history of players online.



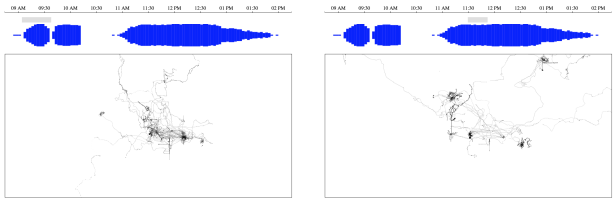
(c) Player position heatmap.

Figure 2: *Realtime statistics and visualizations of player activity, as provided to server administrators and players by the Epilog Dashboard. The units in (a) for* `traveled`, `mined` *and* `placed` *are* blocks*;* `social` *is* time active near other players / time active. *(b) shows the visualized history of online players on a server, with the x-axis referring to time in days (7 days), and the y-axis to the number of players, with a peak of 22 players. Vertical lines mark 6AM local time. (c) shows player positions accumulated over time for a map segment selected by the server administrator.*

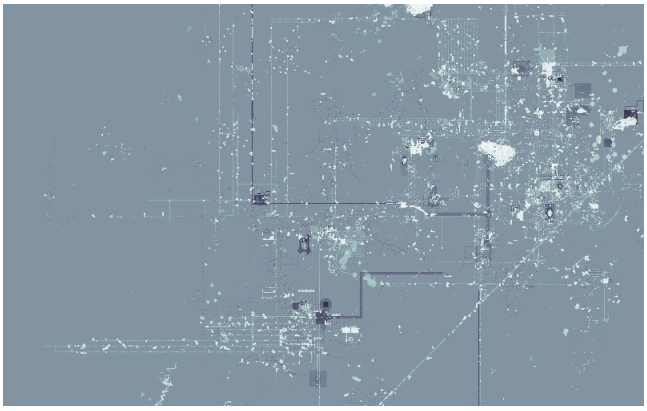
3.2 Map Miner

Map Miner allows server administrators to easily explore data recorded by Epilog, both spatially and temporally. The HTML5 based tool visualizes timelines in combination with heatmaps, providing a convenient way to explore datasets by interactively zooming and dragging both the timeline and the map. A certain time window can be selected and dragged to see the corresponding map data change over time.

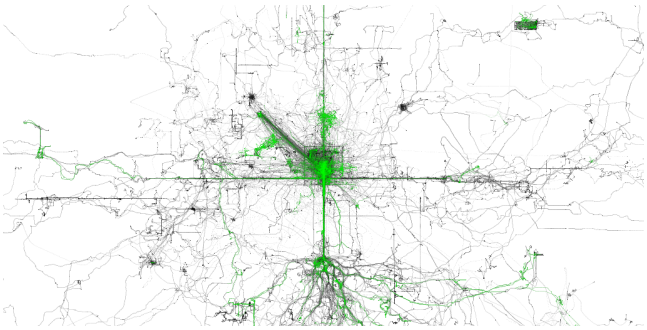
Figure 3 (a) shows Map Miner with the number of active players in the timeline section (blue) and player positions in the map section. The time window, represented by a gray selection bar, is dragged over the timeline in order to observe player dynamics. Other spatial data can be visualized like economic value (b) or player contact (c). Figure 4 shows an additional example for possible timeline content.



(a) Tools for analyzing player behavior spatially and temporally.



(b) Blocks removed (light) and added (dark) over time.



(c) Accumulated player positions with player contact marked green.

Figure 3: *(a) The Map Miner tool enables a server administrator to explore and inspect the data and player behavior temporally (time selection) and spatially (area selection). (b) Heatmap showing player effort by highlighting block movement. (c) Heatmap showing where players meet.*

3.3 Classify

The Classify plugin analyzes the behavior of all online players and annotates the in-game list of players with their current behavior (see Figure 5). Each player is classified in real time, based on his current behavior, into the categories *build* [b], *mine* [m], *fight* [f], *explore* [e] and *idle* [i] according to the classification algorithm introduced in [Müller et al. 2015b]. The plugin allows players to identify similar players for potential collaboration (e.g., finding a player for collaborative mining).

Figure 4 shows an example of a player's behavior over one day. A server administrator has access to this data which provides valuable feedback about player types in the community or how a player's behavior changed over a certain time period.

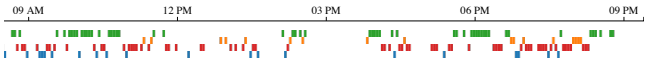


Figure 4: *A player's behavior over one day. The activities are color-coded: mine (green), build (orange), fight (red) and explore (blue).*

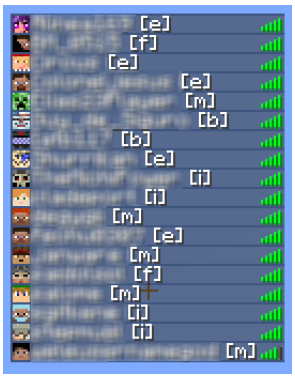


Figure 5: *The player list annotated with build [e], mine [m], fight [f], explore [e] or idle [i] by Classify.*

3.4 Graph Miner

The Graph Miner allows inspection of player interaction and collaboration. Player collaboration reveals information about the community, indicating if players share activities. There are many types of collaboration in Minecraft. Players may build together, share building or farming infrastructures, or protect each other from attacks. They may even fight each other, which can be viewed as a collaborative activity if both parties desire this, since players collaborate to improve their experience of the game. The in-game chat allows players to communicate with others to coordinate activities or to get more information about the environment. We follow the collaboration indicators defined in [Müller et al. 2015a], which are player contact (*Contact Graph*), chat between players (*Chat Graph*) and shared buildings, farms and chests (*Building, Farming, Chest Graph*).

Contact Graph. The contact graph $G_{contact} = \langle V_{contact}, E_{contact} \rangle$ connects with an edge those players that are in contact with each other, where "contact" is made when both players are active and within a certain radius from each other. The threshold distance was determined by a combination of watching individual players, their subjective feeling of "closeness" and inspecting recorded gameplay of collaborating players. The edges are weighted by the sum of all contact durations.

Chat Graph. The chat graph $G_{chat} = \langle V_{chat}, E_{chat} \rangle$ connects players that have been in a conversation with each other. Edges are weighted by the sum of answers given or received between two players.

Building, Farm and Chest Graph. Three graphs are defined by joint usages of buildings, farms and chests. The building graph $G_{build} = \langle V_{build}, E_{build} \rangle$ connects players that contributed to the same building. The edge weight is given by the sum of contributions the player pair has made to the building of interest. Joint farming activity is defined by the farming graph $G_{farm} = \langle V_{farm}, E_{farm} \rangle$, which is constructed analogously to the building graph. The edge weights correspond to the sum of farm accesses of two players to a shared farm. Last, an edge in the chest graph $G_{chest} = \langle V_{chest}, E_{chest} \rangle$ connects two players that use the same

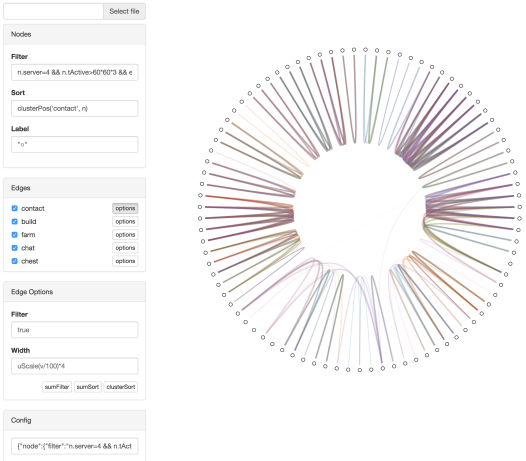


Figure 7: *Interactive visualization and exploration tool for server administrators to explore and analyze collaboration data. The differently colored collaboration graphs are superimposed. The vertices and edges represent players and pairwise collaboration.*

chests. An edge represents the sum of transferred items of two players to a shared chest.

The five aforementioned graphs are shown separately and superimposed in Figure 6. For this example we used data that we have collected on one of the servers with 56 players that have been active for 273 player-hours. The contact graph, for example, contains 86 edges. The graph coverage, given by the number of edges divided by the number of edges of a completely connected graph, is 0.06 and indicates that a player has had contact with 6% of all other players on average. With the GUI that we have developed we provide a convenient tool for exploring different types of player connections (Figure 7).

3.5 DiviningRod

Game analytics utilities help server administrators explore and understand player behavior and the social interactions between players. Based on these findings, subtle interventions may be desired to increase the engagement of players and with that also the fun of playing a particular game level. With the DiviningRod plugin [Müller et al. 2015a] we aimed at improving player collaboration by adding a navigation tool (see Figure 8). DiviningRod provides programmable compasses that can point to other players or to specific locations.

We implemented compasses to locate players by characteristics derived from data collected by Epilog, like play time, contact time with other players and other kinds of behavior. Since the compasses can be provided by a server, they can be created dynamically and use heuristics based on previously collected data or the current game situation. Alternatively, players can locate other players by their name or create new compass targets by writing hashtags on a sign.

4 Discussion

Visualization tools for analyzing player data are very valuable as they help analysts understand various aspects of players and game communities. Our tools, which are integrated into the HeapCraft platform, allow real-time analysis of data and have been used to analyze a large set of player data across many servers.

Figure 8: *The DiviningRod plugin adds navigation tools that aim at improving player collaboration. A stick is programmed to lead to the player with the most experience in exploring, who is currently 2.5 blocks away. Other heuristics to influence player behavior can be easily added and evaluated.*

When and Where to Play. Visualizations showing the history of the number of active or online players over time can be used by players to predict the optimal point in time to join a particular server, based on which type of collaborative experience they prefer. The Epilog Dashboard includes this graphic, which updates in real time. Administrators can include it in their own website. We also offer the data used to generate the graphic, so administrators are able to create their own graphical representations.

We have developed a web-based tool for the exploration of spatial data, timelines and relations between them. Data can be visualized on a timeline which allows selection of time periods. A map then shows spatial data for the selected time. The tool provides a better understanding of what is happening on individual servers by looking at player position maps. Hotspots and areas that are difficult to access or avoided by users can be identified. Both the map and the timeline can be zoomed and dragged to reveal additional details.

Challenge Level. Previous analysis of the data [Müller et al. 2015a] indicates strong correlations between fighting and collaboration. We have anecdotal evidence that some experienced players prefer challenging fights. Increasing a server's difficulty level will make fighting computer-generated monsters harder and could attract more fighters. According to anecdotes from our play tests, DiviningRod is a particularly useful tool for enhancing *player-versus-player* fighting. We observed players using it to observe the distance to their nearest player to either avoid them, prepare themselves for a fight or choose the next player to attack. The ability to locate specific players has also been used for similar purposes. Those new possibilities can make a server more appealing to fighters.

Player Matching. The visualization tools allow for analysis of player collaboration. In previous work [Müller et al. 2015a] it was found that some players are more likely to team up than others. Thus, such visualizations make it easier for players to find potential collaboration partners. Similar players can be found with the Classify tool, which shows, for all online players, if a player is currently building, mining, fighting, exploring or idle. This information can be used to find teammates, or even antagonists, if preferred.

DiviningRod can help players to find specific players they want to collaborate with, or choose a player that is nearby. DiviningRod also supports finding players based on real-time analytics. This enables the implementation of more complex heuristics based, for example, on findings of player pair analyses. Examples include

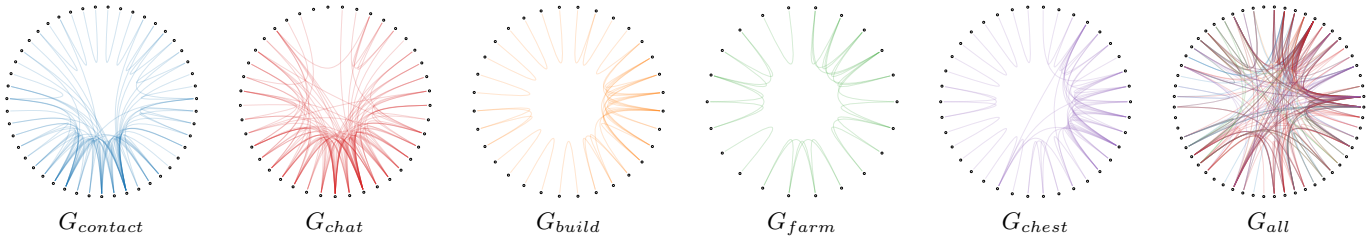


Figure 6: *Graphs showing pairwise collaborative player activity for contact, chat, building, farm and chest measures, as well as the combined graph. The vertices represent players and the edges represent a particular kind of collaboration between two players.*

finding collaborative players or players with a high sense of social responsibility.

Perceived fairness is a common cause of dispute among players. The wealth of players with more play-time on a server is sometimes considered unfair by newcomers. Stealing from other players and destroying their property are common results of trying to counteract that imbalance. This phenomenon is not necessarily a bad thing. Players might enjoy their role as justice fighters, and having to protect property adds interesting aspects to the game. Nonetheless, having greater information on the pro-sociality of other players enables administrators and players to make more informed choices about whether and how to participate meaningfully in these societies. It also highlights possibilities to improve collaboration. New players might feel connected to other newcomers. DiviningRod can help a server's new players find each other. Further studies and evaluations are necessary to analyze the effectiveness of DiviningRod and the various heuristics.

Making data available to other players on how much a player gives and takes from shared resources could increase collaboration. Players could find altruist players more easily and reduce the risk of exploitation by freeloaders. Players might also be interested in improving their own collaboration score, which could benefit the server's community. Contribution scores and a measure for collaboration for individual players could be published on a server's companion website. Alternatively, a tool similar to Classify could be used to indicate collaboration scores in-game.

We introduce a suite of tools for collecting, analyzing and visualizing player data on Minecraft servers. Our focus on collaboration, visual analytics, speed, privacy control and usability make *HeapCraft* uniquely suited to the population with the most to gain from accessible analytics utilities: the community of game players.

Acknowledgements

Richard P. Mann was supported by ERC Advanced Investigator grant 'Momentum' no. 324247 to Dirk Helbing. Severin Klingler was supported by ETH Research Grant ETH-23 13-2. Credit for all Minecraft screenshots and screen capture goes to Minecraft ® TM & © 2009-2015 Mojang / Notch.

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