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HEAPCRAFT: Quantifying and Predicting Collaboration in Minecraft

Stephan Müller¹, Seth Frey², Mubbasir Kapadia^{2,3}, Severin Klingler¹,
Richard P. Mann^{1,4}, Barbara Solenthaler¹, Robert W. Sumner^{1,2}, Markus Gross^{1,2}

¹ETH Zürich

²Disney Research Zürich

³Rutgers University

⁴University of Leeds

Abstract

We present HEAPCRAFT: an open-source suite of tools for monitoring and improving collaboration in Minecraft. At the core of our system is a data collection and analysis framework for recording gameplay. We collected over 3451 player-hours of game behavior from 908 different players, and performed a general study of online collaboration. To make our game analytics easily accessible, we developed interactive information visualization tools and an analysis framework for players, administrators, and researchers to explore graphs, maps and timelines of live server activity. As part of our research, we introduce the *collaboration index*, a metric which allows server administrators and researchers to quantify, predict, and improve collaboration on Minecraft servers. Our analysis reveals several possible predictors of collaboration which can be used to improve collaboration on Minecraft servers. HEAPCRAFT is designed to be general, and has the potential to be used for other shared online virtual worlds.

Introduction

Collaboration is an indispensable aspect of shared virtual worlds, where players work together to achieve common goals. Collaboration is not only what players expect to experience when joining a shared virtual world, it is an indicator for strong communities. Surprisingly, there are no standard measures and predictors for collaboration in shared virtual worlds.

This paper presents HEAPCRAFT: an open-source data collection and analysis framework for recording, monitoring, and improving collaboration in the popular video game Minecraft. Consistent with our general approach of improving collaboration by empowering players, our system democratizes game analytics with a real-time analytic framework that can serve the needs of both researchers and players. We collected over 3451 player-hours of gameplay from 908 players over 43 different servers. While we focus on collaboration, the recorded data can potentially further research on many aspects of player behavior.

We use this data to develop and validate a general collaboration index for quantifying collaboration on Minecraft servers. Significant correlations in our collected data suggest that players increase their amount of collaboration not

by collaborating with the same player more often, but by collaborating longer and with more different players. Players prefer to team up with players showing similar interests in respect to the activities building, mining, fighting and exploring. Differences in experience levels have no effect on the likelihood of teaming up. Collaborative players tend to be more socially responsible by giving more to shared resources than they take. Our analysis yields several actionable ways to increase collaboration on a Minecraft server, which we implement as extensions to our framework, including easy-to-install server plugins for classifying player behavior and finding groups of like-minded players. Finally, HEAPCRAFT is designed to be general and has the potential of being used to study player behavior in other shared online virtual worlds.

Related Work

The first experimental studies of human collaboration were actually motivated by advances in communication technology (Bavelas 1950). Today, online societies and virtual worlds are leveraging the anonymity and low transaction costs of online interaction to motivate innovation in the quantitative study of collaboration.

Collaboration in Shared Virtual Worlds. The online social systems that have attracted the most attention from quantitative collaboration researchers are wikis, massively multiplayer online games, and other shared virtual worlds. Efforts in social virtual world game analytics have yielded many insights into effective player groups (Chen 2009; Ducheneaut and Yee 2013; Chung et al. 2014). The comprehensive game analytics volume (Seif El-Nasr, Drachen, and Canossa 2013) gives some attention to the study of player communities. Computer-supported collaborative work (CSCW) researchers have already begun to recognize the research potential of Minecraft specifically (Wendel et al. 2013; French et al. 2014).

Research on Minecraft. Because of a subtle difference from other popular games, Minecraft has excellent potential to advance research on social phenomena: unlike the most heavily-researched games, most Minecraft servers are hosted and maintained not by the game's ownership, but by players. This difference is important because there are many more independently instantiated Minecraft worlds, each of whose data is owned not by reticent corporations,

but by players who may be eager to contribute to science. Most current research on Minecraft is either qualitative educational research, or more quantitative research on media technology (Garrelts 2014; Schifter and Cipollone 2013; French et al. 2014; Bukvic et al. 2014). Leavitt’s ethnography identifies the social media culture surrounding the game as intrinsic to the experience of it (Leavitt 2013). Though little is officially reported about the demographics of the game, various preliminary surveys have reported median ages of around 19, with approximately 90% of players male (Reddit 2011; Bukvic et al. 2014). This paper leverages our prior contributions (Müller et al. 2015b; Müller et al. 2015a) for statistically classifying player behavior in Minecraft.

HEAPCRAFT

We have developed HEAPCRAFT: a suite of open-source tools to record, analyze, visualize and influence player behavior in Minecraft. These tools, and the datasets they have generated, can be used for purposes beyond the study of collaboration. We briefly summarize the main features of HEAPCRAFT here: (1) **Epilog** is a Minecraft server plugin that records gameplay and sends it to our logging server. (2) The **Epilog Dashboard** is a web-based front-end to provide real-time visualization and analytics to server administrators using the data collected by Epilog. (3) **Classify** is a Minecraft server plugin which classifies a player’s current activity as building, mining, fighting, exploring or idle and shows that information to all players in-game (Müller et al. 2015b); typical results in Figure 1. (4) **Graph Miner** and **Map Miner** are data exploration and visualization tools to inspect player relationships, locations and timelines. Please refer to <http://heapcraft.net> for supplementary material such as videos showcasing our tools, and more details on how to install and use our plugins on your own servers. The concluding section also introduces the **DiviningRod** plugin, a new tool for improving collaboration on Minecraft servers.

Data Exploration

Using the Epilog plugin, we collected 3451 hours of active gameplay by 908 different players on 43 servers over a period of 65 days between March 13, 2015 and May 17, 2015 (defining play as “active” if a player triggered a game event within the last 20 seconds). For our analysis, we restricted this dataset to 15 servers, excluding all servers with less than 10 hours of recorded active gameplay, at the cost of only about 30 player-hours of data. Additionally, within these remaining servers, players with less than one hour of gameplay were excluded from the analyses, leaving 3342 player-hours by 252 players. Table 2 shows the number of players and the combined amount of active gameplay for each server.

Quantifying Collaboration

Many activities in Minecraft are more fun and efficient when pursued with other players, and the game engenders many different types of collaboration. Collaborative players might keep near to each other, construct buildings together, share

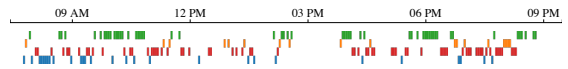


Figure 1: A typical player’s behavior over one day, in terms of mining (green, first row), building (orange), fighting (red) and exploring (blue, last row).

building materials, share farming infrastructures, or protect each other from hostile players and computer-controlled monsters. Miners and explorers benefit from working together by protecting each other from attacks and spotting valuable resources more quickly. Players can participate in shared adventures, in-game chat, and competitions to kill each other for sport. At the simplest level, they may even merely seek company. Shared buildings, farms and chests may signal collaborations that are occurring at one location, but possibly asynchronously, with different players active at different times. True collaborative activity will usually be indicated by several of these specific indicators. A shared building project, for example, might include player contact, collaborative building, chat and shared chests. Because of this diversity of forms of collaboration, we started our attempt at a general collaboration metric with an exploratory analysis comparing several specific collaboration indicators. Where it was necessary to define metrics in terms of in-game parameters, we based the decisions below on the results of game knowledge, exploratory analyses, and a desire to make conservative decisions that minimize the likelihood of “false positive” results.

Collaboration Graphs

We define several primitive collaboration indicators and construct undirected, weighted graphs where the vertices V represent players and the edges E represent a particular kind of collaboration between two players (Table 1).

Contact Graph. Two players are in contact if both are active and their distance becomes smaller than 15 blocks. To connect players that have been in contact with each other, we define a contact graph $G_{contact} = \langle V_{contact}, E_{contact} \rangle$, where edges represent contact between two players weighted by the sum of all contact durations. The resulting graph has 1138 edges across 242 nodes, covering 96% of all players.

Chat Graph. Players often use in-game chat to communicate with players both nearby and far away. The chat graph, $G_{chat} = \langle V_{chat}, E_{chat} \rangle$ connects players who have participated in a shared conversation. We use a simple model to detect conversations where we assume every message is a reply to all messages by other players which occurred up to 20 seconds before the message. This produces false positives by possibly connecting independent conversations. However, players waiting for a reply are likely to read all broadcasted messages which somewhat justifies counting them as being part of simultaneous conversations. The weight of the edges represents the sum of answers given or received between two players. The resulting graph has 1008 edges across 221 nodes, covering 88% of all players. Of course, conversation

Graph	Vertices	Edges	Players without edges
contact	242	1138	10 (4%)
chat	221	1008	31 (12%)
build	191	378	61 (24%)
farm	149	323	103 (41%)
chest	188	435	64 (25%)

Table 1: Number of vertices and edges for the different graphs.

does not imply collaboration, but combined with other noisy measures of collaboration, the chat graph can contribute to a characterization of general collaboration.

Building, Farm, and Chest Graphs. Minecraft offers several in-game constructs, like building, farms, and chests, whose joint usages imply opportunity for collaboration. The building graph, $G_{build} = \langle V_{build}, E_{build} \rangle$ connects players who have contributed to the same building, where a building is defined as 20 or more adjacent building blocks. Each collaborative building creates a complete graph connecting all contributors. The weight of the edges represents the sum of contributions two players have made to the same buildings. The resulting graph has 378 edges across 191 nodes, covering 76% of all players.

To characterize joint farming activity, $G_{farm} = \langle V_{farm}, E_{farm} \rangle$ is constructed analogously to the building graph. The weight of the edges represent the sum of farm accesses (plant or harvest) of two players to a shared farm. The resulting graph has 323 edges across 149 nodes, covering 59% of all players.

Chests in Minecraft can be used to share items among players. The chest graph, $G_{chest} = \langle V_{chest}, E_{chest} \rangle$ contains edges between players who share chests, with edge weights representing the number of items put in or taken out. The resulting graph has 435 edges across 188 nodes, covering 75% of all players.

Observations. Figure 2 illustrates the graphs for player contact, chatting, building, farming, chests, and their union, for one sample server and also for all servers combined. We observe that the 5 graphs often connect similar sets of players, which indicate a correlation between these primitive forms of collaboration, and hint at a general indicator for measuring collaboration. In particular, the contact graph contains large parts of every other graph and is therefore a good candidate to be used for that metric.

The graph completeness is calculated by dividing the number of edges by the number of edges of a completely connected graph. A completeness of 0.2 means a player is connected to 20% of all other players in average. Table 2 shows, for each server in our dataset, the completeness of the contact graph.

We use the function:

$$\text{cover}(G_1, G_2) = |E(G_1) \cap E(G_2)| / |E(G_2)|$$

to express how much of graph G_1 covers G_2 or in other words, how many of the edges of G_2 are also present in G_1 . Figure 3 shows the result of the function for all previously defined graphs. Note that the contact graph contains at least

Server	Player Statistics		Graph Statistics	
	Players	Active (s)	Edges	Completeness
1	65	903.36	617	0.30
2	13	865.75	47	0.60
3	23	344.01	80	0.32
4	56	273.18	86	0.06
5	28	226.68	159	0.42
6	11	227.13	29	0.53
7	7	137.34	12	0.57
8	14	95.74	58	0.64
9	5	73.35	7	0.70
10	14	54.97	25	0.27
11	3	53.14	3	1.00
12	3	30.05	3	1.00
13	4	24.58	6	1.00
14	4	18.13	5	0.83
15	2	14.24	1	1.00

Table 2: Player statistics and completeness of the contact graph on different servers shows the relative sociality of different servers.

		graph 2				
		contact	build	farm	chat	chest
graph 1	contact	1.00	0.80	0.70	0.76	0.71
	build	0.27	1.00	0.51	0.27	0.48
	farm	0.20	0.43	1.00	0.17	0.45
	chat	0.67	0.72	0.54	1.00	0.57
	chest	0.27	0.55	0.61	0.25	1.00

Figure 3: Graph coverage matrix $\text{cover}(G_1, G_2)$; fraction of edges in G_2 also present in G_1 , over all servers.

70% of edges from all other graphs. In order to put the numbers into perspective, we construct a graph representing a typical server. Based on the contact graph, the typical graph contains 47 vertices and 212 edges. Two randomly generated typical graphs have an expected coverage of 20%. Since the coverages of the contact graph are all much higher than 20%, all five graphs must be strong indicators of a shared hidden variable. Since the graphs each represent theoretically unrelated aspects of collaboration, of both synchronous and asynchronous varieties, we believe the hidden variable to indicate collaboration generally.

Collaboration Index

In order to quantify collaboration, we not only need to understand player relationships, but also how to formalize them. The high coverage of the contact graph and the appealing properties of its edge weights make contact time an excellent candidate for quantifying collaboration. Since the contact graph contains large parts of all other graphs, we

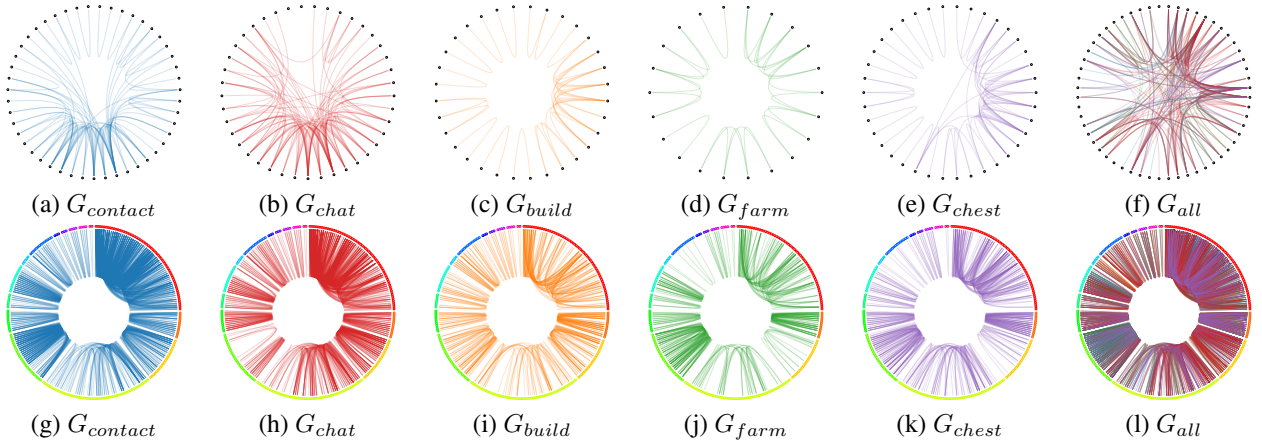


Figure 2: (a) - (f). Graphs showing various forms of collaborative player activities on a popular server. (g) - (l) Combined collaborative player activities on all servers.

define collaboration exclusively in terms of player contacts. Player contacts are easy to interpret, easy to measure, and they co-occur reliably with every other graph’s specialist operationalization of collaboration.

We introduce the collaboration index I_c as an universal indicator for collaboration for players (p) and servers (s) respectively:

$$I_c(p) = \frac{\sum_{e \in E_{contact}(p)} W[e]}{\text{active}(p)}$$

$$I_c(s) = \frac{\sum_{e \in E_{contact}(s)} W[e]}{\text{active}(s)}$$

where $E_{contact}(\cdot)$ represents the set of all contact graph edges of a player or server, $W[\cdot]$ the weight of an edge and $\text{active}(\cdot)$ the duration of active gameplay of a player or server. The collaboration index can be interpreted as a player’s or server’s average number of simultaneous active player contacts. We normalize I_c over the total amount of active gameplay to facilitate comparisons between different players and servers.

Predicting Collaboration

Player Analysis. Our data indicates that players prefer to meet players they already know. Collaborative players are more likely to meet other players and/or meet them for longer, but not more frequently than average players. Collaboration shows a positive correlation with fighting and a negative correlation with mining. To explore the relationship of our collaboration index with other game behaviors, we compared 14 variables, defined in Table 3. Because of the exploratory nature of this analysis, we use systems of pairwise Pearson correlations to establish the significance of these relationships. We limited the number of investigated pairwise relationships and controlled for multiple hypothesis testing by using a low significance threshold of $p < 0.01$. The results of the correlation analysis are illustrated in Figure 4.

Metric	Definition
active	active gameplay in hours
collab	collaboration index (average number of simultaneous player contacts while active)
nContact	number of different players a player has had contact with; indicates player popularity
fContact	average number of contacts with a specific player (frequency)
tContact	average contact duration; indicates player familiarity
chestContrib	shared chest $2 * in / (in + out) - 1$ from -1 (only taking items) to 1 (only putting items in)
farmContrib	shared farm $2 * in / (in + out) - 1$ from -1 (only farming) to 1 (only planting)
farm	average farm usage $(in + out) / active$
chat	average number of chat messages sent $nMsg / active$
b, m, f, e	ratio of 3 minute time slices classified as the one of the following behaviors: (b)uilding, (m)ining, (f)arming, and (e)xplore. The values add up to 1.
special	behavior specialization $\text{Var}(\{\mathbf{b}, \mathbf{m}, \mathbf{f}, \mathbf{e}\})$ from 0 (all behaviors are equally frequent) to 0.25 (only one behavior).

Table 3: Metrics for predicting collaboration.

Since **collab** is defined in a way that should interact with measures of sociality **nContact**, **fContact** and **tContact**, comparing the values of their respective correlations is interesting. **Collab** vs. **nContact** and **collab** vs. **tContact** show high correlations whereas **collab** vs. **fContact** shows no significant correlation. This means collaborative players meet more other players and/or meet them for longer, but not more frequently than average players. **collab** shows strong positive correlations with fighting and negative correlation with mining.

Contribution to Common Goods. Collaborative players tend to be more socially responsible by giving more to shared resources than they take. By default, players who develop resources like productive farms or well-stocked chests

	active	collab	nContact	fContact	tContact	farm	chat	b	m	f	e	special
active		-0.12	0.29	0.76	0.1	0.06	-0.01	0.17	0.05	-0.12	-0.06	-0.16
collab	0.07		0.31	0.02	0.36	-0.11	0.22	-0.2	-0.23	0.34	-0.04	0.06
nContact	0	0		0.12	-0.22	-0.11	0.08	-0.05	-0.2	0.29	-0.13	-0.1
fContact	0	0.72	0.06		0.17	0.18	0.06	0.14	-0.01	-0.12	0.01	-0.09
tContact	0.11	0	0	0.01		0.04	0.1	0.17	0.01	-0.07	-0.07	0.08
farm	0.37	0.09	0.08	0	0.49		-0.05	0.17	0.12	-0.09	-0.13	-0.12
chat	0.89	0	0.2	0.38	0.1	0.42		-0.18	-0.22	0.29	0	0.27
b	0.01	0	0.39	0.03	0.01	0.01	0		0.05	-0.53	-0.34	-0.15
m	0.41	0	0	0.91	0.92	0.05	0	0.39		-0.28	-0.43	-0.36
f	0.06	0	0	0.07	0.24	0.14	0	0	0		-0.41	-0.07
e	0.34	0.52	0.04	0.9	0.26	0.04	1	0	0	0		0.44
special	0.01	0.33	0.1	0.14	0.2	0.05	0	0.02	0	0.29	0	

Figure 4: Correlations between player variables (upper triangle) and p-values with $p < 0.01$ high-lighted green (lower triangle).

can do little-to-nothing to prevent others from benefitting from them. This scenario incentivizes players to extract from common goods without contributing to their maintenance. So players who continue to contribute to common goods are exhibiting prosocial behavior. We analyzed two types of common goods: Chests and farms accessed by more than one player each. Our dataset contains 193 players with shared chests and 184 players with shared farms.

Among the 134 players using both shared chests and shared farms, there is relatively strong correlation between both contribution types ($r = 0.22$, $p = 0.01$). Players have been observed storing what they farmed in chests and taking seeds to plant from chests, which would suggest a negative correlation. Shared chests and farms are public goods, contributions to which are cooperative and prosocial, and we speculate that the positive correlation between these activities is caused by a hidden linked variable indicating a player’s sense of social responsibility. The strong correlation between **collab** and contribution ($r_{chest} = 0.19$, $r_{farm} = 0.16$, $p < 0.05$) is particularly impressive since there is no easy way for a player to identify another player as a benefactor or a freeloader.

Player Pair Analysis. Players prefer to team up with players with similar preferences in building, mining, fighting and exploring whereas differences in experience are irrelevant. We calculate whether the player contact pairings increase or decrease the variable differences compared to random pairings. \mathbf{vVar} is calculated as follows:

$$\mathbf{vVar} = \text{Var}(\{v_{p1}, v_{p2}\}) = (v_{p1} - v_{p2})^2/4$$

where v stands for one of the previously defined variables and p stands for one of the two players. The average change

active	collab	farm	chat	b	m	f	e	special
0.06	-0.12	-0.12	-0.17	-0.19	-0.21	-0.32	-0.31	-0.2

Figure 5: Average change in entropy dQ from player contact pairs compared to random pairings.



Figure 6: A compass provided by DiviningRod showing the distance (1 meter) to a player-created sign.

in entropy dQ is calculated as follows:

$$dQ = (E[\mathbf{vVar}] - \mu)/\sigma$$

where μ, σ represent the mean variance and standard deviation across all possible player pairs. Our results shown in Figure 5 indicate that players prefer to team up with similar players, especially in respect to fighting and exploring. The low value of **active** implies that differences in experience level are not important for predicting that two players will collaborate.

Improving Collaboration

We identify actionable ideas on how to improve collaboration on a server based on correlational insights derived from our data analysis. These are introduced as extensions to HEAPCRAFT which can be used by server administrators to help improve the communities on their servers.

Plugins. The Epilog Dashboard, Classify plugin, and DiviningRod plugin all provide information that, according to our findings, may improve collaboration on a server. In particular, we created DiviningRod to actively influence player collaboration by making it easier to meet and work with other players. DiviningRod adds a wide variety of different compasses to Minecraft. They can point to players, places, or player-hashtaged locations (Figure 6). The target of a compass can be defined on a per-player basis using real-time heuristics provided by our logging server. Researchers can implement their own heuristics and evaluate their effect on players. We collect usage statistics on what kind of compasses are used when, for how long and by whom. We tested DiviningRod by installing it on our own server. The most popular features include locating the nearest player, locating players by username, and finding a server’s spawn point. More details can be found at <http://heapcraft.net>.

Recommendations

Based on our analysis, we outline the following recommendations to help improve collaboration on Minecraft servers,

and highlight HEAPCRAFT functionality that implements these suggestions.

Promote Simultaneous Activity. Our data highlights the importance of many players being online at the same time. The Epilog Dashboard includes a visualization of the number of active players over time, which administrators can include on their own websites so that players can predict good times to play.

Facilitate Fighting. Although counterintuitive, our data indicates a strong correlation between fighting and collaboration. DiviningRod has proven to be a useful tool for “player vs. player” fighting. We observed players using it to track nearby players, toward both offensive and defensive ends.

Improve Player Matching. Our analysis of player collaboration pairs show that some players are more likely to team up than others. Making it easier for players to find good partners could improve collaboration. DiviningRod can help players find other ‘like-minded’ players with similar styles of play, and it also supports finding players based on real-time analytics. This enables the implementation of more complex heuristics based on findings in our player pair analysis. Examples include finding collaborative players, identifying social responsible players and, as Classify shows, determining whether a player is currently building, mining, fighting or exploring. All of this information could be used to find effective teammates.

Indicate Contributions. According to our analysis, collaboration is correlated with contributions to common goods. We assume players prefer collaboration with altruists than egoists. Perceived fairness is a common cause of dispute among players, but the game provides no easy way to determine the extent of a player’s egoism. 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 their exposure to freeloaders. Players with automatic ratings of their collaborativity and prosociality might then work to improve their rating, to the benefit of the whole server’s community.

Conclusion

Using a dataset of over 140 player-days of behavioral data, we derive the collaboration index, a universal indicator of collaboration based analysis of different aspects of collaboration in shared virtual worlds. The collaboration index provides a convenient way of comparing amounts of collaboration between different players or servers, and can benefit both researchers and server administrators.

Our data analysis revealed several possible predictors of collaboration. Players are more likely to collaborate with players they already collaborated with, and with players of similar type. Players increase their amount of collaboration not by collaborating with the same player more often, but by collaborating longer and with more different players. We also found collaborative players to be more socially responsible by giving more to shared resources than they take.

We propose several actionable ways to improve collaboration in shared online worlds. Implementing these insights, we developed DiviningRod, which provides players with

programmable social compasses. It can be used to help players find other players based on heuristics found to improve collaboration. Additionally, we continue collecting data and expect to gain access to data from even more servers in the future. Our datasets on shared virtual worlds will be a valuable asset for new studies in social science.

Limitations and Future Work. At present, our suggestions for improving collaboration are based on correlational insights. Field experiments and user studies based on DiviningRod and other HEAPCRAFT tools will allow us to improve the rigor of our prescriptions. The possibility of controlling the tool remotely opens the possibility of conducting a wide variety of social experiments “in the field.” If adoption of HEAPCRAFT continues at only the present, modest, rate, we will have data on 250 servers in the next twelve months. At that point, we will have sufficient data to characterize differences in prosociality, collaboration, and community at the server scale.

Generalizing to Other Virtual Worlds. HEAPCRAFT is designed to be general and can be extended to other online virtual worlds, not just Minecraft. The Epilog plugin was authored as an interface between game-specific data collected during in-game activities and the rest of the tools used for visualisation and analysis. Game features such as the possible use of shared chests lead to game-specific measures of collaboration. These features will not necessarily be present in other virtual worlds, and new features will need to be included in their place. However, the basic principle of identifying the possible space of low-level actions, and then querying players on their self-perceived behavior to classify high-level behavior remains sound. As we extend the framework to other worlds, we expect that key commonalities will emerge that make the entire system of data collection, visualization and analysis more portable.

One key reason for our selection of Minecraft is the community-centered approach to gaming – individual server administrators maintain their own worlds, makes rules, and actively collaborate with players to maintain the worlds the community desires, while advertising their servers on public directories. A potential difficulty in porting our framework to other worlds is greater propriety control in other games, which may necessitate greater cooperation with game owners. We hope that one effect of our work will be to demonstrate to game owners the potential benefits of an open approach to improving user experiences with widely accessible behavioral data.

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