The Social Shape of DUST: Learning Networks in Alternate Reality Games

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Abstract
Alternate reality games (ARGs) are powerful learning environments due to the way that they inspire collaboration and bring a participant's day-to-day life into play. An important aspect of educational ARGs is that learning is social, with players sharing information and resources across a network of other players. In the following poster we provide analysis of gameplay data from a large-scale ARG, DUST, centered on science learning. We examine the metric of eigenvector centrality (EC) as a way of predicting meaningful learning networks in ARG play, expand upon that finding with a qualitative case study of a highly involved player, and offer the possibility of EC monitoring during gameplay as a way of improving player outcomes in future ARGs.
Keywords: Social network analysis; alternate reality games; digital youth; information behavior; distributed learning
doi: 10.9776/16535

Acknowledgements: Thank you to the National Science Foundation for the funding to conduct this research, and to all co-designers and players who made our work possible.
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1 Introduction

Alternate reality games (ARGs) are increasingly recognized as powerful sites of collaborative learning (Bonsignore et al., 2012). This poster reports on analysis from one such ARG project: DUST. DUST was an educational ARG that ran from January to April of 2015. The narrative focused on the efforts of a group of teenagers to avert an existential threat to life on Earth, which had caused the world's adults to all pass out, leaving teenaged players and characters to solve a series of scientifically and ethically based problems. We present data related to social network analysis (SNA) of the bonds formed between players, in-game characters, and gamerunners.

We focus on a specific metric within the DUST social graph: *Eigenvector Centrality* (EC). EC is a way of measuring connectedness within a graph that can be compared to degree centrality (DC). Whereas degree centrality is an unweighted count of how many connections (i.e. friends) a node has, EC takes into account the comparative weight of those connections as part of an iterative calculation over many passes across the network (Bonacich, 2007).

We find that EC represents the learning network that a player has formed. Recognizing this metric as an ongoing aspect of play can allow gamerunners to connect players to meaningful information networks. We include a mixed SNA and qualitative analysis as a novel means of understanding learning networks in ARGs.

2 Theoretical Framework

SNA can allow researchers to observe patterns and relationships in social situations, which would be otherwise invisible in traditional quantitative or qualitative approaches (Hansen, 2014). In systems of networked learning, SNA allows researchers to understand the shape of interaction between learners, facilitators, and objects, giving a crucial analytic lens on questions of legitimate peripheral participation (Lave & Wenger, 1991) in the learning process (De Laat et al., 2007).

Our theoretical basis for assessing learning in DUST relies heavily on social learning literature, with an emphasis on our players' pathways through informal science education based not only on their interest and skills with STEM topics, but also with developing affinities, identities, and literacies, which can be thought of as lines of practice that draw learners into science fields (Gee, 2007; Azevedo, 2011).

A key component of ARGs is that they spread information and gameplay across a wide variety of modalities and give players a central role in assembling that information together as they apply diverse skill sets to make sense of what is occurring in the game. Important to the task of participatory play are designer-run characters known as 'protagonists by proxy', as well as gamerunners who play as themselves. Both act as models and motivators for authentic engagement with the learning content of the game (Bonsignore, et al., 2013).

The main platform of the game was built with social learning in mind, and allowed our players to establish friend connections between fellow players and, importantly, *our protagonists by proxy and gamerunners*. Our analysis offers a preliminary understanding of the shape of social learning for a particular player. Her case also serves as a potential model for follow-on analysis of the learning trajectories of her fellow players and the DUST player community overall. Our approach may be useful not only to future designers of educational ARGs but also to designers and moderators of similar multimodal, distributed communities of learning.

3 Methodology

For our analysis we used a mixed methods approach with SNA serving as a way of finding larger patterns in the data, and qualitative analysis being used to ground those patterns in context (Creswell & Plano Clark, 2006; Rotman et al., 2012). We structured our data so that each user represents a single node within the graph, and each edge represents a friend relationship. The arrow of directionality reflects who sent and received the friend request.

Throughout the game our research team conducted weekly meetings, part of which involved identifying and discussing key players. As the game concluded and we began to focus more heavily on data analysis, we generated a shortlist of key players. SNA was one of the analytic techniques we used both to direct deeper qualitative examination of key players and to corroborate (i.e., triangulate, Yin, 2014) themes that emerged from other gameplay data (e.g., peer awards, badges earned, posted content, etc.). Using the SNA metric of EC, we noticed that many of our qualitatively identified key players were showing up in both lists.

We present our initial round of findings from a focused SNA of the player community. We expand upon these initial findings by doing a deep qualitative analysis of a single case within that list of high EC users (Yin, 2014). The qualitative data for our case study is drawn from contributions by our focal participant, K4Ren, along with interview data, field notes from our research team, and artifacts from the game itself. We integrate both streams of data - SNA and qualitative analysis - by creating a richer network graph using metrics culled from our qualitative work. For example, we find that K4Ren often conversed with a central protagonist by proxy character, Violet. Although Violet's connection with K4Ren is equal with any other entity in the graph in our initial analysis, it becomes much stronger through our new qualitatively derived metric, thereby changing the shape of K4Ren's learning network established within the game.

4 Findings

For our analysis we used a mixed methods approach with SNA serving as a way of finding larger patterns in the data, and qualitative The figure below shows two tables for comparison, one using total degree (which factors total connections) and EC (which runs an iterative measure of quality among those connections). In contrast, another player, Jman, shows up highly on total degree, but much lower on EC. Jman was a player who made many friend connections, but ended up contributing very little to the game itself.

TOP PLAYERS (TOTAL DEGREE)

#	Tot. Degre	Degree In	Degree Out	Name	Role
1	67	54	13	IRIS	Game Master
2	59	37	22	Lia	Proxy Player
3	45	29	16	Violet	Proxy Player
4	42	1	41	Jman	Player
5	37	0	37	MK1	Player
6	33	22	11	Jay	Proxy Player
...	...	...	...	...	...
18	20	15	5	K4Ren	Focal Player

TOP PLAYERS (EIGENVECTOR CENTRALITY)

#	Eig. Cent.	Name	Role		
1	1	IRIS	Game Master		
2	0.779	K4Ren	Focal Player		
3	0.779	Lia	Proxy Player		
4	0.776	Raven	Player		
5	0.582	Cat12	Player		
6	0.592	Seeven	Player		
...	...	...	...	...	...
105	0.035	Jman	Player		

Figure 1. Comparison Chart of SNA Metrics. Game Master refers to the central artificial intelligence character who posted regular updates and hints for players; Proxy Players are characters designed for the purpose of serving as models and guides alongside players; and Players are our registered users who participated in the game.

The above figure shows that a raw count of friendships (represented with total degree) is an unreliable metric of success in the game. However, EC helps to identify a number of our key players among the top spots of the list. Independently our research team highlighted these players as being vital to the progress of the game during our weekly debriefings, prior to any social network analysis.

A next SNA step that we can take is to consider the ego-centric network of our focal player, K4Ren. We look at the connections that she had formed through her time with the game. Her egocentric network at the end of the game is presented below.

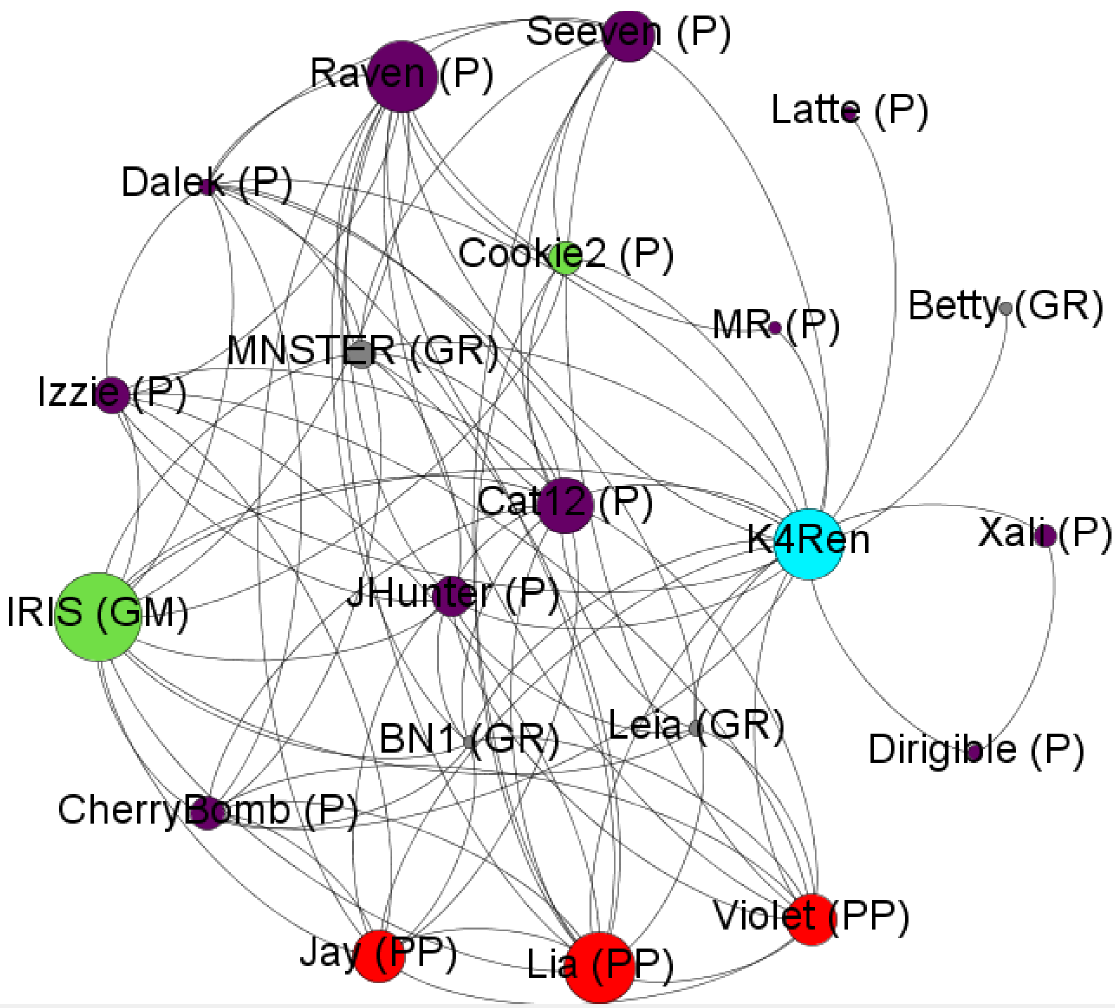

Figure 2. K4Ren's Egocentric Network. This graph describes all of the nodes that she has connected with by the conclusion of the game. The letters in parenthesis represent the role that node played in the game - GM is Game Master (an artificial intelligence character that was responsible for distributing key information), PP is a proxy player, GR is a gamerunner (often a design team member, or undergraduate volunteer), and P represents a player. Nodes are sized by EC.

In addition to lending itself to SNA, our platform has two research-minded features built in: player statistics, as well as player feeds. Player statistics list the total interactions quantitatively for each player, and the feed provides a minute-by-minute account of player activity that can be analyzed qualitatively. Figure 3 presents a key interaction from K4Ren, depicting one way that information travels within her learning network (Fig. 2).

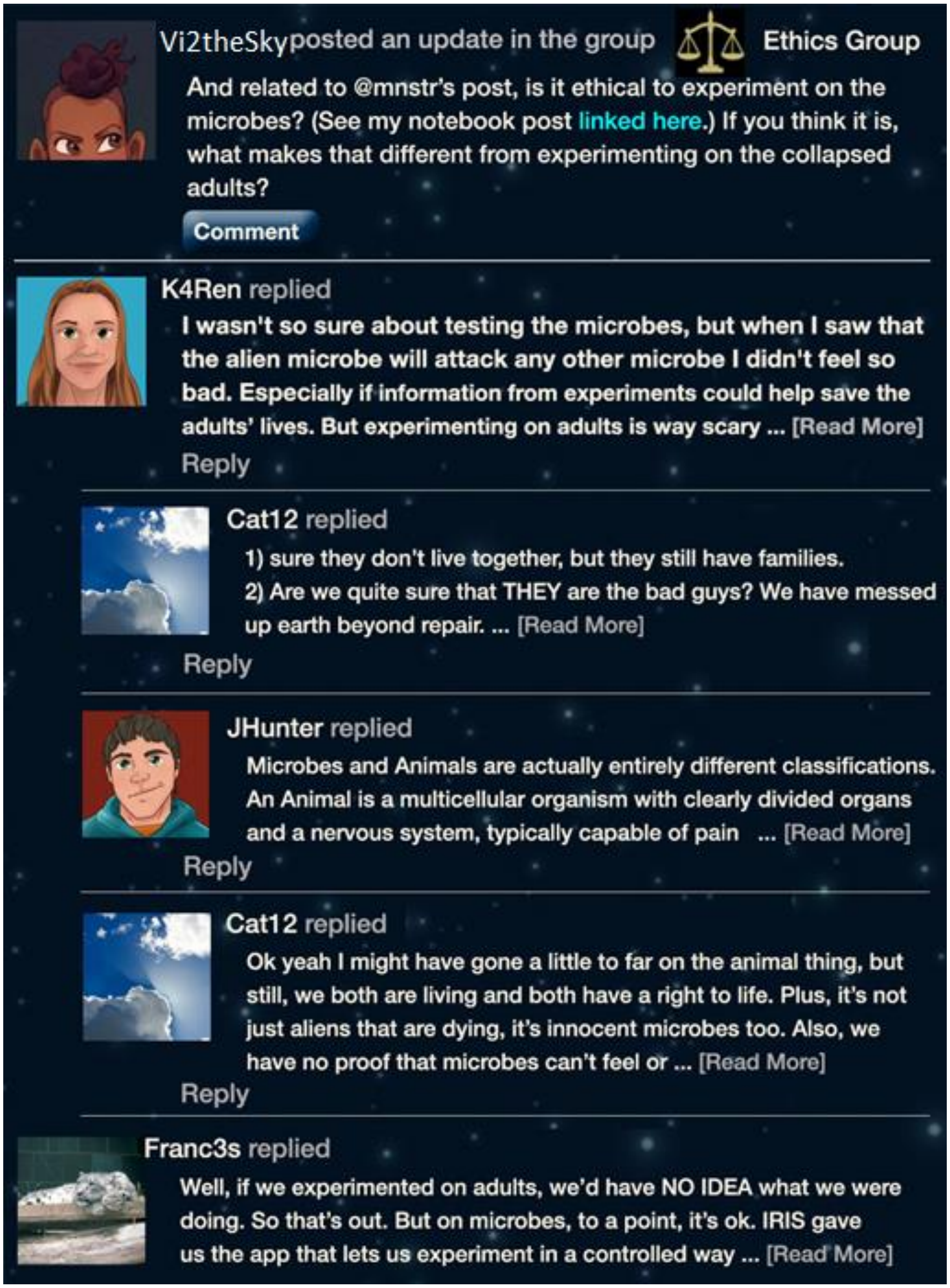

Figure 3. Sample Player to Player Interaction. K4Ren engages in a conversation that she has seen from her involvement in the Ethics Group. Here she is involved with a number of players in her direct egocentric network (JHunter and Cat12), as well as a player outside of her direct network (Franc3s).

5 Conclusions

We have presented data derived through both SNA and qualitative means. In our full poster we will refine existing edges with more detail from player interaction. From Figure 3, for example, we will expand on interactions with Violet (who K4ren is responding to), Cat12, and a player who isn't part of K4Ren's direct friend network, Franc3s. Importantly, our analysis will factor in *groups and artifacts*, providing a greater idea of how technical affordances play into learning networks.

Authentic learning in an educational ARG involves collaboration, interacting with real-world situations, and asking players to see themselves in the game rather than an avatar. Our poster expands on existing SNA methods of participation in ARGs (Ruppel, 2012) by applying models of social learning through qualitative analysis. We also provide valuable findings for future designers of ARGs regarding the formative role that gamerunners, proxy players, and social affordances (e.g. groups) can have in players' learning network formation.

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