

## Modeling Group Dynamics in Virtual Worlds

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### Abstract

In this study, we examine human social interactions within virtual worlds and address the question of how group interactions are affected by the game environment. To investigate this problem, we introduced a set of conversational agents into the social environment of Second Life, a massively multi-player online environment that allows users to construct and inhabit their own 3D world.

Our agents were created to be sufficiently lifelike to casual observers, so as not to perturb neighboring social interactions. Using our partitioning algorithm, we separated continuous public chat logs from each region into separate conversations which were used to construct a social network of the participants. Unlike many groups formed in communities and workplaces, groups in Second Life can be rapidly-forming (arising from few interactions), persistent (remaining stable over a long period), and are less affected by socio-cultural influences.

### Introduction

Massively multi-player online games and virtual environments provide new outlets for human social interaction that are significantly different from both face-to-face interactions and non-physically-embodied social networking tools such as Facebook and Twitter. We aim to study group dynamics in these virtual worlds by collecting and analyzing public conversational patterns of Second Life users.

Second Life (SL) is a massively multi-player online environment that allows users to construct and inhabit their own 3D world. The physical environment in Second Life is laid out in a 2D arrangement, known as the SLGrid, with each region hosted on its own server and offering a fully featured 3D environment shaped by the user population. Users control avatars, through which they are able to explore different environments and interact with other avatars in a variety of ways. One of the most commonly used methods of interaction in Second Life is basic text chat.

Unlike many groups formed in communities and workplaces, groups formed in virtual environments can be rapidly-forming (arising from few interactions), persistent (remaining stable over a long period of time), and less affected by socio-cultural influences. In this project, we exam-

ine the regional differences in Second Life, focusing on examining the differences between groups formed in activity-specific regions and in other types of regions. To quantify these differences engendered by different regions, we measure statistical characteristics of the network as a whole, analyzing actors and relations rather than egocentric actors and attributes.

### Prior Work

Second Life is a unique test bed for research studies, allowing scientists to study a broad range of human behaviors. For instance, social scientists have used Second Life to study norms and etiquette in dressing and meeting people (Friedman, Steed, and Slater 2007). Several studies on user interaction in virtual environments have been conducted in SL including studies on conversation (Weitnauer et al. 2008) and virtual agents (Bogdanovych, Simoff, and Esteva 2008). (Zhao and Wang 2008) describes a technique for simulating multiple agents in a virtual environment using a hierarchical model of cognition and decision making.

### Approach

To conduct our study of group social interactions in Second Life, we had to address the following subproblems:

1. creating chatbots of sufficient realism to record public conversations without perturbing existing social interactions;
2. partitioning unstructured dialog into separate conversations;
3. identifying social network structures from the partitioned data;
4. comparing entire social networks from different regions.

There is little related work pertaining to problems (2) and (4); necessitating the development of new approaches to solve these problems.

### Bot Construction

Figure 1 shows the overall data collection architecture. Multiple bots, stationed in different SL regions, listen to all the messages within their hearing range on the public channel.

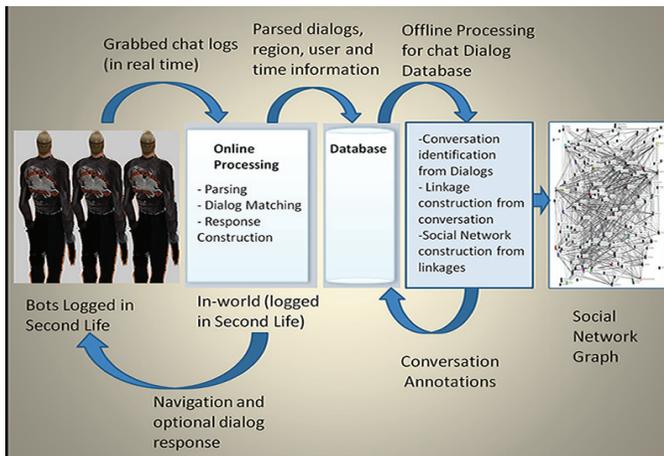


Figure 1: Multi-agent architecture for Second Life data collection

To add variability to the responses, we gave the bot the ability to generate a message based on randomly selecting a series of “response components”, that form a message when pieced together. The bots forward chat messages to the server, which parses and conditions messages for storage in the dialog database. Occasionally the server sends the bots navigational commands and optional dialog response if the communication was directed to the bot. Linkages between SL actors are inferred offline by partitioning the unstructured data into separate conversations; these linkages are used to construct the graphs used in the social network analysis.

## Data Collection

To collect data on social interactions in Second Life, we launched eight agent bots (each with a different Second Life account and avatar) in eight regions, over several consecutive days and randomly selected 5 days of data for analysis.

Determining social interactions from unstructured chat data alone is a difficult problem. The earlier work in dialog management has been done primarily for a particular context (Orkin and Roy 2007) and in question-answer format rather than in open-ended dialog. Dialog analysis has been previously explored within the Restaurant Game (Orkin and Roy 2007), where a corpus of human dialog is collected and leveraged to improve the realism of the bot’s dialog in a social situation. Unlike the bot in the Restaurant Game, our bot must operate in a broader range of multi-person social situations, rather than the well-defined single-user social scenario. Our conversation partitioning algorithm (not shown here for brevity) separates the data into time intervals (called sessions), which are then partitioned and organized into a hierarchical structure. Each session, marked by a start and an end time, denotes an interval during which a user was chatting. The messages that make up a session are determined by finding consecutive chat messages from a user with less than 20 minutes between any two of the messages.<sup>1</sup> This will not

<sup>1</sup>In Second Life, users who are inactive for 20 minutes are automatically disconnected.

always guarantee that each session represents an actual chat session, but it provides a logical cut-off point that can be used to obtain reasonably accurate results. While the start time is not null, the following process is repeated for each of the users in each region (separately): 1) the end of the session with that start time is found; 2) the session marked by that start time and that end time is added to the user’s list of sessions; 3) the start time is set to the time of the next message from the same user and region after the current end time.

## Social Network Analysis

Using the information extracted from the raw chat logs, we construct social networks of the users in each Second Life region monitored by the bots. Social network analysis is commonly used to describe and visualize social interactions among groups of people. In our analysis we focus on the network as a whole, analyzing actors and relations (vs. egocentric actors and attributes). Communications between actors are represented as undirected links, rather than representing sending and receiving chat messages as separate links. To analyze group dynamics in different Second Life regions, we look at the following measures: 1) univariate statistics and 2) centrality measures.

**Univariate statistics** A statistical view of the social network data describes the data as consisting of a sample of some larger population of possible observations. Relationship measures are viewed as probabilistic realizations of an underlying tendency of relationship strengths. The *mean* of the tie strength can be calculated considering the network as a whole and taking the mean of all tie strengths over the entire adjacency matrix containing all of the actors in the network. To evaluate the hypothesis that this mean value is zero (indicating a lack of true social connection), we perform a zero mean test and use it as a screening method to eliminate from consideration those networks that are composed of random communications between actors.

**Measures of centrality** An alternate method to analyze networks is to calculate the centrality measures of nodes in the network, which correspond to how connected nodes are to other nodes. To facilitate statistical analysis, we selected a continuous measure of centrality, *betweenness*. Betweenness, in the context of binary data, examines actors based on their presence on the geodesic paths between pairs of other actors in the network. The more people the actor is connected to the greater its betweenness, discounting for all the indirect links to other actors.

## Results

Our method of social network analysis differs from most of the existing work in that we perform the comparison of social networks with different users and no common attributes rather than performing a comparison between the same actors and different attributes, or different networks and the same attributes. Our goal is to compare different social networks, rather than different actors.

We use four methods of comparison for the social networks. First, we calculate univariate statistics—the mean

Table 1: Description of regions selected for analysis.

Region Name	Region Description
Help Island Public	An orientation area for new users. A densely populated region with many user social interactions with users offering help.
Mauve	A sandbox for users to try scripts and build objects. Social interactions are focused on users' commenting/seeking other users
Morris	A entertainment-oriented region with a sandbox, a maze, fun houses, and boating.
Moose Beach	A densely populated newbie friendly beach environment.
RezzMe	A sandbox and shopping area, along with resources like building classes.
Help People Island	Similar to Help Island Public, but with fewer people, and more focused on assisting users than with socializing.
Kuula	Heavily social sandbox area.
Pondi Beach	Beach environment resembling Australia, includes places for sitting, dancing, gaming

value and standard deviation of the linkage matrix of the network. The mean value indicates the density of the network (amount of linkages) and standard deviation, shows the variation in the linkages across actors. Next, we use the hypothesis tests for the mean value as a basis of comparison for the networks as a whole. Then we do an analysis of betweenness over all the nodes in the population and compare the networks using a non-parametric test.

We obtained conversation data from eight different regions in Second Life over fourteen days of data collection (80,183 total utterances). A general description of the activities that the users tend to perform in each region is shown in Table 1. The regions fell into three different general categories: 1) orientation areas for new users to learn how to interact with Second Life, 2) sandbox areas that permit users to experiment with building construction, and 3) general entertainment areas (e.g., beaches). To study the effects of regional differences/similarities on social interactions, we performed the above mentioned four analyses on the following two datasets:

- an aggregated dataset of multiple days of data from one region visualized in a single network;
- a series of partitioned datasets with each day's communication data divided into a separate network.

### Univariate Network Statistics

Table 2 gives the value of the univariate statistics for each region (Day 1). These network statistics convey important information about the characteristics of the network and are calculated from the adjacency matrix, ignoring the diagonal values. A high mean value indicates high network density. Similarly, a high standard deviation (SD) indicates that there is a large amount of difference in linkages between actors.

Table 2: Regional univariate statistics (Day 1)

	Help Island Public	Help People Island	Kuula	Mauve	Moose Beach	Morris	RezzMe	Pondi Beach
Mean	0.6	0.5	0.7	0.3	0.3	2.4	0.7	0.5
SD	4.6	2.8	6.6	3.2	3.2	5.9	5.0	3.8
Min	0	0	0	0	0	0	0	0
Max	192	39	351	53	74	20	118	61
Obs.	72630	4032	28056	1482	8190	42	13572	10302

Table 3 gives the mean hypothesis results for the same data set for all the regions using a 5% significance level. We use a zero mean hypothesis test to filter out the regions for which the null hypothesis is true, indicating that any ties among actors are due to chance. The results indicate that Mauve, Morris and RezzMe are those regions for which the null hypothesis is true at 5% significance level. The columns give the results of using a hypothesis test to determine whether the mean of the region shown in the column is equivalent to the mean value of the region that appears as the row value. A ✓ indicates that the null hypothesis is true (the two means are the same) and a X otherwise.

By examining the univariate statistics over all regions and days, we observe the following trends:

- Sandbox regions usually exhibit a low mean value and high standard deviation suggesting a low and irregular pattern of communication, which is understandable as most of the users are busy in construction activities. The test for the mean hypothesis further confirms this belief, as all the sandboxes (Mauve, Morris and RezzMe) are observed to have a statistically significant similarity to a mean value zero.
- The standard deviations on orientation islands range from within normal standard deviation values (suggesting regular pattern of communication between users) to high standard deviation values (suggesting greater interaction among few users.) Orientation islands are mostly populated by new users are more comfortable talking to the few people they engage with initially.
- The recreation areas have standard deviation values suggesting regular pattern of communication among the users with about half of the users engaging in communication.
- Orientation and recreation areas have statistically similar mean values, indicating that overall the strength of the communication ties among the actors is similar in pattern for both regions of this type. There is a large amount of socializing in these regions and more chance of dialog exchanges between users.

### Centrality Measure

An alternative to using mean values to measure the connectedness of nodes in the network is the *betweenness* centrality measure. Table 4 shows the K-S test (Massey, Jr. 1951) results. These tests were performed on aggregate networks built from conversational utterances across all days. The abbreviation NN denotes the number of nodes. A ✓ indicates

Table 3: Mean Hypothesis Test for Day 1.

	Help Island Public	Help People Island	Kuula	Moose Beach	Pondi Beach	Mean
	M	M	M	M	M	
Help Island Public	N/A	✓	✓	✓	✓	0.561
Help People Island	✓	N/A	✓	✓	✓	0.510
Kuula	✓	✓	N/A	✓	✓	0.655
Moose Beach	X	X	X	N/A	X	0.553
Pondi Beach	X	X	X	X	N/A	0.521

Table 4: K-S test results for aggregate valued data.

	Help Island Public	Help People Island	Kuula	Mauve	Moose Beach	Morris	Rezz Me	Pondi Beach	
	B	B	B	B	B	B	B	B	NN
Help Island Public	N/A	X	✓	X	✓	X	X	✓	299
Help People Island	X	N/A	✓	X	✓	X	X	✓	769
Kuula	✓	✓	N/A	X	✓	X	X	✓	344
Mauve	X	X	X	N/A	X	X	✓	X	135
Moose	✓	✓	✓	X	N/A	✓	✓	✓	117
Morris	X	X	X	X	✓	N/A	✓	✓	320
RezzMe	X	X	X	✓	✓	✓	N/A	✓	75
Pondi	✓	✓	✓	X	✓	✓	✓	N/A	265

that the K-S statistics were significant at the 5 percent alpha level for the null hypothesis (that the two distributions come from the same continuous population) and a **X** indicates otherwise. The social networks based on the day partitioned data show more similarity across regions than the networks created from the aggregate data (results not included for brevity). NN denotes the node count and ✓ indicates similarity and a **X** indicates otherwise. We also performed a similar comparison of social networks from the same region across different days (not shown). We note the following:

- Less similarity in betweenness was observed in aggregated data than in the day-wise data across the different regions.
- Social networks for the same region are similar across multiple days and across multiple sampling points.
- Disappointingly, no definite conclusion can be made about activity-specific regional differences based on betweenness alone.

If we look at the results across different activity-based regional categories, we observed that beaches (entertainment areas) are similar to orientation areas in most instances for all the five days of dataset. Similarly there is considerable similarity in one of the help islands (Help People Island) and one of the sandbox regions (RezzMe) for the five day data set. So betweenness alone is not a good predictor of the activities commonly performed in a region.

## Conclusion and Future Work

From our analysis of the regional and temporal structure in social networks, we conclude that there are significant regional characteristics in the social networks formed from conversations in Second Life that remain stable over time. Univariate statistics appear to be good predictors of these regional differences whereas the betweenness centrality measure fails to capture this variation.

The creation of a rich computational model of emergent large-scale group dynamics in virtual worlds should benefit researchers working on a broad range of problems, such as developing non-player characters for massively-multiplayer online games and creating agent-based simulations with realistic social interactions (Shah, Bell, and Sukthankar 2009). Although most earlier studies on group dynamics (Shi and Huang 2004) have been conducted on individuals connected by long-standing social interactions, a key finding is that humans form groups that exhibit group behavior patterns and biases within a few seconds of minimal interaction, even without face-to-face contact or prior history. In future work, we plan to do a detailed comparison of the social networks mined from Second Life with those constructed from other sources of data such as blogs, social networking sites, and RSS feeds to better understand the differences between such social networks and those emerging in the virtual world of Second Life.

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