Finding Your Social Space: Empirical Study of Social Exploration in Multiplayer Online Games

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***Abstract*—Social dynamics are based on human needs for trust, support, resource sharing, irrespective of whether they operate in real life or in a virtual setting. Massively multiplayer online role-playing games (MMORPGS) serve as enablers of leisurely social activity and are important tools for social interactions. Past research has shown that socially dense gaming environments like MMORPGs can be used to study important social phenomena, which may operate in real life, too. We describe the process of social exploration to entail the following components 1) finding the balance between personal and social time 2) making choice between a large number of weak ties or few strong social ties. 3) finding a social group. In general, these are the major determinants of an individual's social life. This paper looks into the phenomenon of social exploration in an activity based online social environment. We study this process through the lens of the following research questions, 1) What are the different social behavior types? 2) Is there a change in a player's social behavior over time? 3) Are certain social behaviors more stable than the others? 4) Can longitudinal research of player behavior help shed light on the social dynamics and processes in the network? We use an unsupervised machine learning approach to come up with 4 different social behavior types - Lone Wolf, Pack Wolf of Small Pack, Pack Wolf of a Large Pack and Social Butterfly. The types represent the degree of socialization of players in the game. Our research reveals that social behaviors change with time. While lone wolf and pack wolf of small pack are more stable social behaviors, pack wolf of large pack and social butterflies are more transient. We also observe that players progressively move from large groups with weak social ties to settle in small groups with stronger ties.**

***Index Terms*—Social Exploration, Social Behavior Typology, MMORPG, Clustering**

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Fig. 1: Process of social exploration: finding out one's social aspirations.

I. Introduction

Social dynamics are based on human needs for trust, support, resource sharing irrespective of whether they operate in real life or in a virtual setting [1]. Massively multiplayer online role-playing games (MMORPGS) offer an activity based environment facilitating a rich social setting. MMORPGs facilitate collaboration [2], and more importantly, community experience and social acceptance. Users engaging in such a setting can easily fulfill their social needs virtually [3] and may also gain meaningful long term relationships in real life [4]. An important theme within online socializing research literature, is the formation of communities and groups [5], [6]. However, there is a step that precedes joining and socializing within or outside a group. The process of social exploration can be understood as social self-discovery and helps an individual understand their own social needs [7]. It includes the following components: (Figure 1) 1) finding the balance between personal and social time 2) making a choice between large but weak social ties or few strong social ties. 3) finding a social group. The process of social exploration has been studied in sociology and organizational behavior, which looks into patterns of relationships, learning, integration into a social group of new comers in a work place [8] and when an individual needs to change their social group [9].

We use a data-driven approach to study the process of social exploration of players in a multiplayer game through the lens of the following research questions:

- *First, What are the different types of social behaviors?.* We identify 4 intuitive social player types based on the degree of socialization in the game, which are distinct from each other.
- *Second, are certain social behavior types more stable compared to others?* We observed that certain behavior states are more stable while others are more transitory.
- *Third, Do social behaviors of players change over time and are there any discernable patterns of how each of the behaviors evolve with time?* The idea behind this is to identify patterns of behavior change. Experimental results show that some behavior pathways are more traversed than others.
- *Lastly, can longitudinal research of in-game social behaviors shed light on the social dynamics that exists in the network?* The key idea behind this line of investigation is to analyze social behaviors over time and any discernable patterns of changing behaviors that are indicative of a social phenomenon. Patterns of social behavior change suggests that players move from large, weak-tied groups to smaller and more cohesive groups with stronger ties.

To the best of our knowledge, no other work in literature has studied the exploration process of socialization in an online environment, social behavior types and behavior evolution using a data-driven approach.

II. Related Work

Communities in social networks have garnered the attention of recent researchers to study various social phenomena. They serve as excellent testbeds for research in social behavior as they have a huge market, millions of users and provide various individual, group and global activities [10]. Social interactions were found to be an important factor for the enjoyment of MMORPGs and added greatly to the appeal of this genre of games [4], [11]. A large number of studies have focused on virtual communities in an MMORPG setting, specifically, evolution of communities [12], community structure [5], [6] and different roles of players within a virtual community [13], [14]. A deeper knowledge of social behavior of players and their in-game activities can also be used to throw light on various real life human activities that are similar to a lot of in-game activities (e.g economic activities, socialization, networking etc) [15], [16]. Longitudinal research can also help understand how behaviors evolve overtime [17], [18] and can bring forth the social dynamics at play in the network. In literature, many studies have proposed different player typologies, which are based different factors like demographics [19], psychographics, in-game behavior, play styles [20], [21] , motivations [16], [22], in-game demographics [23]–[25] and more recently on game dynamic preference [26].

Several data driven approaches to behavior categorization have been proposed. These include unsupervised clustering algorithms (e.g. k-means, c- means, Ward's Linkage), Non-negative Matrix Factorization (NMF) [27], Self-Organizing Networks (SOM) [28], [29]. [30] applied k- means clustering and Archetypal Analysis (AA) to two datasets and compared their performance. Their analysis revealed that centroid seeking k-means is useful in gaining behavioral insights for the overall population and AA is useful in detecting extreme behavior types. Methods like PCA and NMF generated behavior clusters that were not interpretable within the rules of the game [31]. It was also found that AA and k-means performed similarly when generating behavior-based clusters.

There is, however, not enough research that looks into social behaviors or evolving social behaviors of users in an online social setting. Thus, the need for longitudinal studies to study behavior arises. From a business perspective, it is essential for CTR folks, designers, user experience and player experience specialists to be informed of changing player behaviors and tailor their strategies to accommodate changing behaviors. This ensures long term engagement and enjoyment of players [32].

III. Methodology

A. Data Description

A massively multiplayer online role-playing game (MMORPG) is a genre of video games. They are set in an imaginary virtual world with a multitude of characters in a role-playing setting. Players can create digital avatar, with several customization options like gender, race, appearance, profession and skills to choose from. Progression in MMORPGs involve several in-game activities like character upgrades, quests, loots, combats etc. Games in this genre consist of a large number of players logged into the game environment and interacting socially with other players, thus, facilitating rich a social environment [17]. These in-game activities are logged as player activities making them excellent testbeds for social research and have indeed garnered a lot of attention from recent researchers. Studies have shown that MMORPGs enable human learning through character role-playing and narrative structure [33]. Social elements in MMORPGs are an important aspect of the game and influence engagement and enjoyment. A high number of players also end up making real life friends with people they meet through the game [19].

Data from MMORPG - *Sony Everquest II* [34] was used for the study. The game data is available in the form of player activity logs, which was hosted on four servers. For the purpose of our analysis, we used data from the *guk* server. The different in-game social relationships include granting access to their house to another player, mentoring another player, trading of in-game items, chatting and grouping. As a player levels up within the game, the quests become progressively more difficult.

B. Creation of Groups from Player Logs

For the purpose of this study, we selected 4 consecutive weeks randomly from the player logs. We used logs from week 14 through week 17 (April 3rd, 2005 - April 30th, 2005). Thus, the total observed history period (T) - 4 weeks, One might argue for a longer period for analysis, however, 4 weeks is the natural cycle for a subscription-based model in *Everquest II*. A consequence of the subscription model is that a high number of players also churn at the end of their subscription. Hence we took 4 weeks of data to achieve a significant sample size. The player logs contain information of individual game activity like, kills, leveling up, score increments etc. but had no explicit group information. Although, the player logs were fundamentally missing group information, they did record group size. Therefore, if a player played as a part of a group, the logs showed group size >1. We were able to construct groups of players that logged the exact same values of server name, log time, location id, group level and group size. Identification of such group instances helped us arrive at social metrics of an individual player.

C. Defining Feature Set

We define a social player as a player who engages in any group activity with other players during observation period (Δt). In this time, a player can have some solo sessions as well where they do not play with any other player. Then the total no. of sessions is defined as the sum of total no. of group sessions and total no. of lone sessions. Total number of sessions is an indicator for the level of engagement a player has with the game. We use number of sessions as a measure of engagement instead of total time because it helps quantify player engagement better. Consider a player playing a single long session which may have the same quantitative value as another player playing multiple short sessions. In this case, the second player is more engaged than the first one and is better suited for behavior analysis and longitudinal research. The operational definitions of various elements used in the methodology are as follows:

- *Total observed history (T)* - 4 weeks.
- *Unit of analysis* (Δt) - The basic unit of time used for the analysis was 1 week. One might argue for a longer unit of time to analyze behavior, but we use 1 week as unit of time for our analysis as we observe behavior changes described in a later section at a granular level.

Thus, at any point of our analysis, $\Delta t = week\ i$ and $i \in \{0, 1, 2, 3\}$

- *Session length* – For the purpose of this study, we define a session as a series of activities separated by no more 30 minutes. The same definition of sessions has been employed in some previous studies [19], [35] on the same dataset. Using this definition of session, we define session related metrics for each player which are described below.

We calculate various socialization and engagement metrics for every individual player for each of the 4 weeks.

- *No. of Group Sessions* - This feature denotes the total no. of sessions in $weeki$, which were played in groups, i.e. sessions where group size > 1 in player logs. A high no. of group sessions indicates high level of socialization for a player.
- *No. of Lone Sessions* – This denotes the total number of sessions where a player played alone, i.e. sessions where group size = 1 in player logs.
- *Total No. of Sessions* – This is calculated as the sum of group sessions and lone sessions.

Finally, we compute the feature set for each player based on socialization metrics with the help of variables we defined above. This is done for each week.

- *No. of Neighbors* – Total no. of unique players a player played with, in group size > 1.
- *Fraction of Group Sessions* – Ratio of group sessions to total no. of session. This denotes the fraction of total time is spent by a player in socializing.
- *Average Tie Strength*- This feature defines the ratio of the no. of group sessions of a player in a week to the total no. of neighbors they have in the same week. A lower tie strength indicates that Player X plays with a lot of people but has a weak connection with its immediate neighbors. Therefore for an individual player,

$$Tie\ Strength = \frac{Total\ Number\ of\ Group\ Sessions}{Total\ Number\ of\ Neighbours}$$

We only take engaged social players who have total no. of sessions > threshold value τ for each week, which is defined as:

τ = μ *(log (total no. of sessions)) –* σ *(log(total no. of group sessions))*

where μ denotes mean and σ denotes standard deviation.

D. Clustering

Clustering is one of the most popular unsupervised learning methods used in behavior analysis [29]–[31]. To get an idea of the number of naturally occurring clusters in the dataset, the *elbow method* was used. We plot *within cluster sum of squared errors (SSE)* against the number of clusters as shown in Figure 2. To get an estimate of the optimal number of clusters (k) one might look at the *elbow* of the curve. In this case, we take k = 4. Next, we used k-means to find behavior clusters. The reason for using a hard-clustering method like k-means as our clustering algorithm is twofold. First, we wanted to quantify each cluster. Second, we also study the evolution of player behavior in the next section and therefore avoid amorphous clusters that could make behavior change less visible. Table I shows the cluster centroids for the first week of observed history.

IV. Results And Discussion

A. Player Behavior Types ($btypes$)

Based on the characteristics of the centroids from k-means, we suggest 4 social behavior types ($btypes$).

- **Lone Wolf (LW):** This player type interacts with a small number of other players as compared to the other player types (mean of 6.82 neighbors) and spend a larger percentage of time playing alone. The average tie strength is highest compared to the other types (mean of 2.63). In other words, such players have a very few strong connections.
- **Small Pack Wolf (PWS):**: This player type interacts with a smaller number of other players as compared to

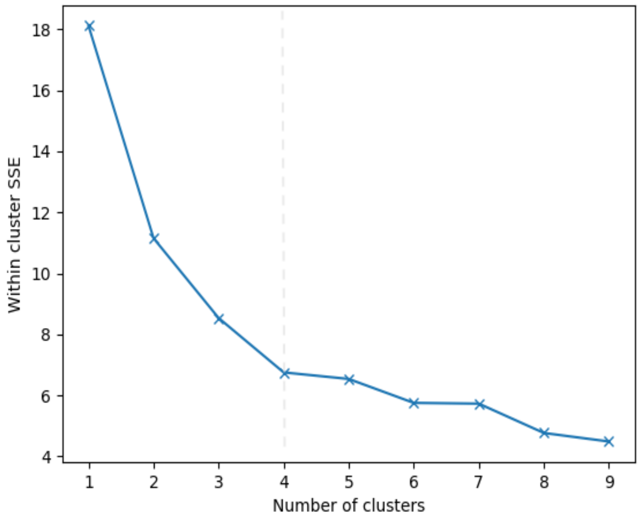

Fig. 2: The elbow method for determining the optimal no. of clusters for k-means. We find that 4 is the elbow of the curve.

TABLE I: Player behavior type based on k-means centroids - Week 14.

		Cluster Centroids		
Player Behavior Label	**No. of samples**	**No. of Neighbors**	**Fraction of Group Session**	**Average Tie Strength**
Lone Wolf	2706	6.82	0.46	2.63
Pack Wolf of Small Pack	1223	26.35	0.60	0.87
Pack Wolf of Large Pack	549	58.86	0.63	0.41
Social Butterfly	137	115.04	0.67	0.29

a Large Pack Wolf player (mean of 26.35 neighbors) but the average tie strength is more that of a Large Pack Wolf player (mean of 0.87).

- **Large Pack Wolf (PWL):** This player type interacts with a smaller number of other players as compared a Social Butterfly (mean of 58.86 neighbors) but the average tie strength is more that of a Social Butterfly (mean of 0.41).
- **Social Butterfly (SB):** This player type interacts with a large number of players (mean of 115.04 neighbors) but the average tie strength is quite low (mean of 0.29) with other players. In other words, such players have a lot of weak connections.

B. *Player Behavior Evolution*

In this section, we study the evolution of social behaviors over time and what, if any, are the common pathways of behavior change. We u to understand the social dynamics of players in *Everquest II* using the following questions:

1) *Are certain social behaviors more stable than others?*
2) *What are the most common trends / pathways/ trajectories of social behavior change for each player type?*

We observe a total of 1862 social players who stayed in the game for 4 weeks and analyzed behavior changes for the duration. We note behavior clusters they belonged to for each of the 4 weeks, as calculated by the method described in the previous section and see if there is a change in the cluster type they belong to for the following weeks. We plotted players as nodes in Figure 5, Figure 6, Figure 7 and Figure 8 to show types of behaviors they exhibit each week. The density of nodes for each behavior type, in a given week, gives a measure of number of people belonging to that behavior cluster type. For example, we see that players who start out as lone wolves in $week1$ of observed history transform their behavior in $week2$, with the maximum number of players staying as lone wolves. A few of them also do show PWS or PWL behavior and extremely few show SB behavior in the $week2$.

Here, we would like to introduce the idea of a *Player Behavior Path* - $Bpath$. A behavior path for n weeks is defined as a tuple of size n where each entry represents the behavior observed in the corresponding week. This is given by:

$$(BPath)X = (btypeX_i, btypeX_{i+1)}, \dots btypeX_n)$$

where $btype \in \{LW, PWS, PWL, SB\}$, and $btypeX_i$ is the social behavior of player X in $week\ i$. We say that Player X has changed their behavior in the following week if $btypeX_i \neq btypeX_(i+1)$. In other words, if a player shows different behavior in the following week, we mark a change in behavior. From our preliminary analysis, we find that there is indeed a change in player social behavior over time. Approximately 50% of the players changed their social behaviors from $week0$ to $week1$. Figure 4 shows the empirically 4 most common $Bpaths$ traversed. Looking at $Bpaths$ for players can be helpful in identifying how one navigates through a social environment. It can also help identify periods of high and low social activity and help in an overall personality assessment of an individual. We will look at how each type of behavior changes with time and what are the most traversed $Bpaths$ in detail below.

Behavior evolution of lone wolf (LW): This behavior type can be understood as a small group of players with high tie strength with one another. We observe from Figure 4 that 42% of the players who started out as lone wolves in $week0$ remain as lone wolves throughout $week1, week2, week3$, $Bpath = (LW, LW, LW, LW)$. From Figure 5 we can see that the density of players showing this behavior in $week0$ does not change drastically in the following weeks when compared to other behavior types. Qualitatively, this could mean that lone wolf is a behavior type that is inherently not very social or this behavior type is exhibited by players who successfully completed the process of social exploration and settled into a group that suits their social needs. We also observe from Figure 4 that LW behavior changes to PWS state and return back to being LW or remain as PWS. Changing to a more social behavior could be because it is challenging to complete difficult tasks or quests alone.

Behavior evolution of pack wolf of small pack (PWS): This behavior is characterized by small number of neighbors, but higher tie strength with its neighbors than pack wolf of large packs and social butterfly. Figure 4 shows behavioral evolution of players who started out as pack wolf of small pack in $week0$. After lone wolf behavior, described above, this is the most stable behavior state. Figure 6 shows the dispersion of players showing PWS behavior in $week0$. Most players who started out as PWS in $week0$ change

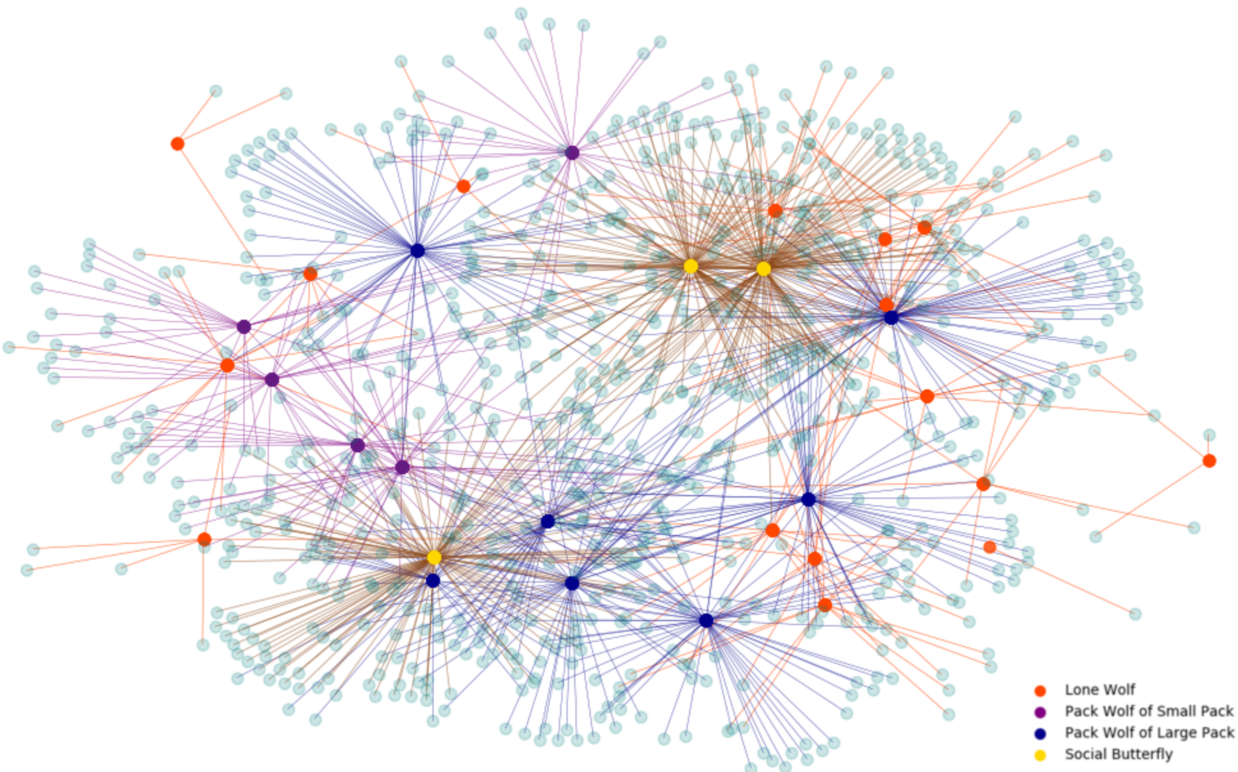

Fig. 3: Network diagram showing 4 types of social behaviors. Lone Wolf (LW) behavior type operate in small social groups. Pack Wolf of Small Pack (PWS) have larger groups but are strongly connected. Pack Wolf of Large Packs (PWL) and Social Butterfly (SB) are characterized by lot of weak ties.

to lone wolf behavior or remain the same by the end of $week3$ irrespective of their $btypes$ in $week1$ and $week2$. Our analysis revealed that 8.9% of the people who started out as PWS continue to be PWS in the following weeks, i.e $Bpath = (PWS, PWS, PWS, PWS)$. Furthermore, 56.5% of the players exhibited behaviors which represent the same or lesser degree of socialization in the following weeks. Table II also suggests that players with high social activity in the initial weeks also gravitate towards this social behavior state.

Behavior evolution of pack wolf of large pack (PWL): This behavior type has a high degree of socialization and ranks only next to social butterfly (SB). Figure 4 shows the common paths taken by people who exhibit this behavior from $week0$ to $week3$. 37% of the players who started out as PWL change their $btype$ to PWS and 33% remain as PWL from $week0$ to $week3$, irrespective of their $btypes$ in $week1$ and $week2$. 8% of the players of $btype$ PWL in $week0$ remain to be of the same $btype$ in the following weeks, $Bpath = (PWL, PWL, PWL, PWL)$. In the following weeks, 49.0% of the players exhibit behavior $(btype)$ that either represents the same degree of socialization (PWL) or less (PWS) but do not show lone wolf (LW) behavior and 22.6% of the players switched to a behavior that was either the same or more social (PWL, SB). Qualitatively, the data suggests that players who start out with this behavior, enjoy a high degree of socialization. They play with a large number of people and maybe part of different groups. Players showing this behavior type have a fairly high degree of socialization but do not have very strong ties with their neighbors. A large group might be helpful in overcoming particularly hard quests.

Behavior evolution of Social Butterfly (SB): This behavior is characterized by high degree of socialization as can be seen in Table I and Figure 3. However, it is the least stable behavior state. We see that 18% of the players who started out as $btype$ social butterfly (SB) remain as social butterfly at the end of $week3$, irrespective of the $Bpath$ traversed. We see from Figure 8 that the density of players showing this behavior in $week0$ becomes more and more sparse in the following weeks as they transition into a behavior state which is characterized by lesser degree of socialization. Even though this is a transient behavior state it is not an unimportant one. This state could be a good starting state for players where they engage with many different groups and people to figure out their social aspirations. This helps them decide how much they want to socialize and which group do they fit the best in. Playing with a large number of groups could also get them acquainted with different in-game strategies, techniques, play styles and also aid in information diffusion. Another way to look at this can be that, as an extreme form of social behavior, social butterfly (SB) state is not sustainable over time. This could be a behavior a player shows when looking to shift to a new group to play with or when their previous group or group

Week 14	Week 15	Week 16	Week 17	Percentage of No. of *Bpaths* per *btype*
LW	LW	LW	LW	42%
	PWS	LW	LW	10%
	LW	PWS	LW	10%
	PWS	PWS	LW	7%
PWS	LW	LW	LW	13%
	PWS	PWS	LW	10%
	PWS	PWS	PWS	9%
	PWS	LW	LW	7%
PWL	PWS	PWS	PWS	9%
	PWL	PWL	PWS	8%
	PWL	PWL	PWL	8%
	PWL	PWS	PWS	6%
SB	PWL	PWL	PWL	12%
	PWL	PWL	PWS	7%
	SB	PWL	PWL	7%
	SB	SB	SB	7%

Fig. 4: Social behavior evolution paths ($Bpaths$) for each behavior type from week 14 to week 17, representing the 4 most common $Bpaths$, which were empirically observed. Other $bpaths$ were not as significant and have not been shown here.

members have left the game (churned).

C. Social Dynamics of Settling into a Group

Our analysis on evolution of different social behaviors shed light on some interesting social dynamics at play in the network. In this section we address the research question, *Can longitudinal research of social behaviors shed light on social dynamics that exist in the network?* Our data suggests that the game network has a number of strong and weak ties, as can be seen in Figure 3. The data in Table II, shows that 82% of the players who started out as $btype$ SB in $week0$ change behaviors to a behavior type characterized by a lower degree of socialization. Furthermore, we observe, that 56% of the players starting out as $btype$ PWL also exhibit behavior that is less social in the following weeks. Players with $btype$ LW in $week0$ are relatively more stable and have the same behavior overtime. However, it is rare that a less social behavior transitions into a more social behavior. This suggests a social dynamic which seems to indicate a process of “social settling in”, wherein a player figures out the degree of socialization needed and the group they want to socialize with. Highly social behaviors like PWL and SB are good starting states, where the degree of socialization is large and points of contact are many. Such states serve many purposes in a player’s life cycle. Firstly, it might help players learn important game strategies and skills from different players. Secondly, it is an important step for the process of social exploration and helps players figure out their social needs like,

1) *Extent of socialization*: What is the split between social time and alone time?
2) *Breadth of socialization*: How many people do they want to socialize with?
3) *Depth of socialization*: What kind of ties do they want with their neighbors - weak or strong?

Lastly, it also helps players know which social group do they want to continue playing with and eventually settle with one that suits their social needs. This choice can be based on the social descriptors mentioned above. In summary, there is a shift in the degree of socialization of an individual player from high to low. In other words, a player actively moves from a large and weak-tied social space to a smaller and strong- tied one. This can be understood as the culmination of the social exploration process. At the end of this process, a player settles into a stable group of his liking and displays stability for some time.

V. Conclusions and Future Work

This paper examines different social behaviors in an MMORPG - Everquest II. First, we look at how people socialize in the game and come up with behavior types based on social metrics using k-means clustering. We suggest 4 types of social behaviors based on the characteristics of the k-means

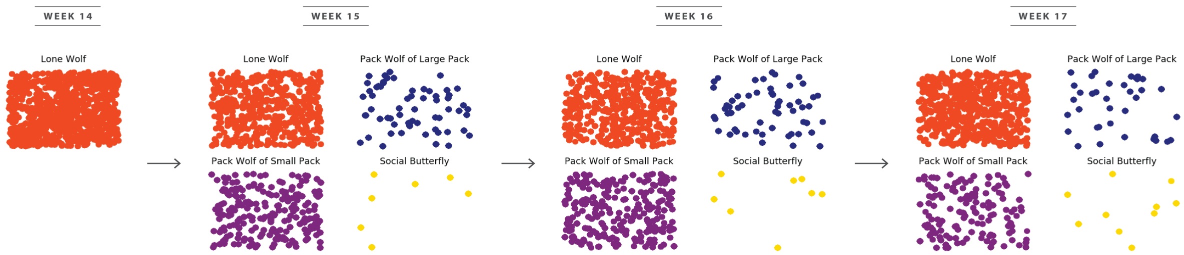

Fig. 5: Social behavior evolution of players who started out as Lone Wolves (LW).

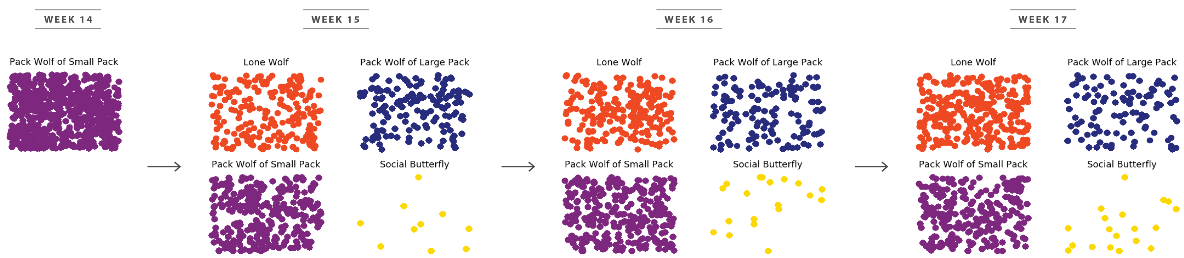

Fig. 6: Social behavior evolution of players who started out as Pack Wolves of Small Pack (PWS).

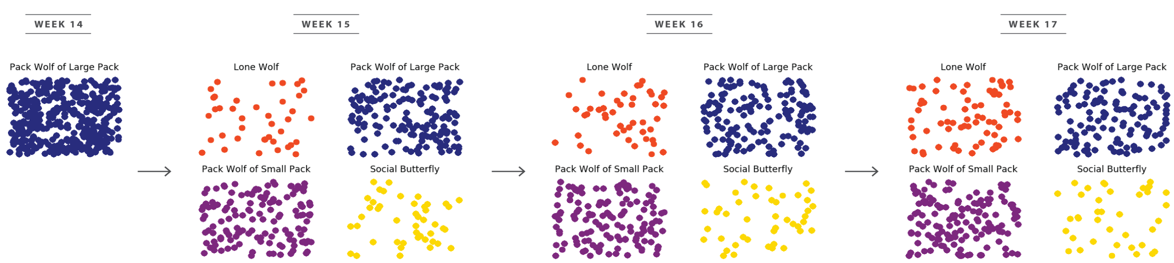

Fig. 7: Social behavior evolution of players who started out as Pack Wolves of Large Pack (PWL).

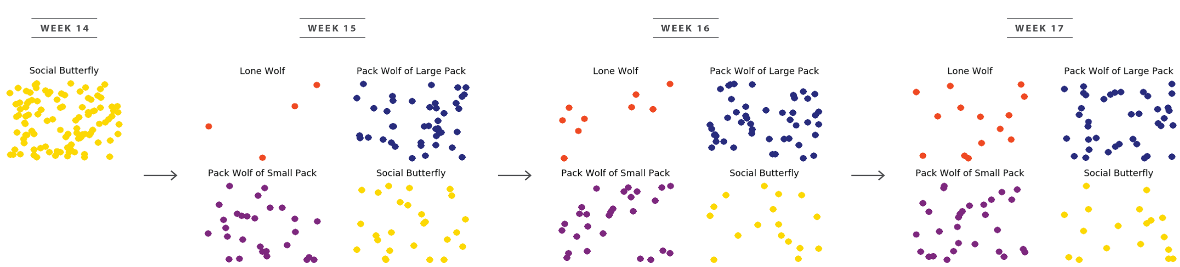

Fig. 8: Social behavior evolution of players who started out as Social Butterflies (SB).

TABLE II: Starting Social behavior type (week 14) and final behavior type (week 17) for each behavior type.

Week 14 Labels	**Week 17 Labels**			
	LW	PWS	PWL	SB
LW	74.9%	18.7%	5.0%	1.3%
PWS	43.7%	37.7%	15.7%	2.9%
PWL	19.19%	37.3%	32.9%	10.5%
SB	14.0%	29.0%	39.0%	18.0%

clusters. We also examined behaviors longitudinally with the purpose of uncovering any trends in behavior change. By looking at the common trends in behavior change, we conclude that there is a process of 'social settling in' operating in the network. Behavior types ($btype$) Social Butterfly(SB) and Pack Wolf of Large Pack (PWL) form the initial and transitional phases of social self-discovery. Here, the players begin the process of social exploration and figure out their social needs. Transitioning into Pack Wolf of Small Pack (PWS) and/or Lone Wolf (LW) marks the culmination of the process, where a player settles down with a group and exhibits stable behavior for some time. A bigger sample size might be needed to arrive at statistically significant most traversed behavior paths ($Bpaths$). We think this could be an on-going process, as would be the case when some players from a small pack or lone wolves leave the game or no longer want to socialize with their earlier group. There are several open-ended questions that surfaced with the study. One is finding out the optimal time duration that the process of social settling in takes. Another is, to investigate whether different social personality types take different amounts of time to settle into a social group. We leave such questions as avenues for future research.

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