

Unveiling Group Characteristics in Online Social Games: A Socio-Economic Analysis

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ABSTRACT

Understanding the group characteristics in MMORPGs is important in user behavior studies since people tend to gather together and form groups due to their inherent nature. In this paper, we analyze the group activities of users in Aion, one of the largest MMORPGs, based on the records of the activities of 94,497 users. In particular, we focus on (i) how social interactions within a group differ from the ones across groups, (ii) what makes a group rise, sustain, or fall, (iii) how group members join and leave a group, and (iv) what makes a group end. We first find that structural patterns of social interactions within a group are more likely to be close-knit and reciprocal than the ones across groups. We also observe that members in a rising group (i.e., the number of members increases) are more cohesive, and communicate with more evenly within the group than the ones in other groups. Our analysis further reveals that if a group is not cohesive, not actively communicating, or not evenly communicating among members, members of the group tend to leave.

Categories and Subject Descriptors

J.4 [Computer Applications]: Social and behavioral sciences;
H.3.5 [Online Information Services]: Web-based services

Keywords

MMORPG; Online Social Game; Group Characteristics; Group Activity; Social Interactions; Socio-Economic Analysis

1. INTRODUCTION

It is reported that tens of millions worldwide enjoy Massively Multi-player Online Role-Playing Games (MMORPGs) as of 2013. An MMORPG typically offers its players rich virtual environments where they can engage in various real-world-like interactions including combats, trades, and conversations with others. Given the complexity, variety, and longevity of the virtual worlds, user experiences in MMORPGs are expected to be close to real life ones.

The realistic virtual environments of MMORPGs opens up new opportunities for researchers to understand complex human behaviors. That is, a game space in an MMORPG is deemed as a large

scale virtual laboratory for observing the socio-economic behaviors of humans. The landscape of user behavior studies like sociology or psychology has been changed by the proliferation of online services including online social networks (OSNs) and MMORPGs [?, ?]. Since MMORPGs provide real life-like environments where users can experience various social interactions like communications, co-operations, economic activities, and so on, there has been an increasing interest in analyzing various activities in popular MMORPGs [?, ?, ?, ?]. For example, [?, ?] investigated various kinds of social interactions (e.g., friendship, conversation, trade) among users in MMORPGs.

Although the above studies on MMORPGs reveal valuable insights into the social interactions among users, most of these studies paid little attention to the social interactions in a group (or a community), rendering the following research questions: *How groups are structured by people? How a user interacts with another in a group? What are the differences among groups in terms of diversity of social interactions or economic activities? How groups evolve and why? Why people leave a group? What makes a group rise and fall?* We argue that understanding the dynamics of group-focused activities in MMORPGs is important in human behavior studies since people tend to gather together and form groups due to their inherent nature both online and offline.

Aion is an MMORPG run by NCSoft, which is a leading online game service provider. With the collaboration with NCSoft, we seek to address the above questions comprehensively, which have not been thoroughly investigated to our knowledge. To this end, we analyze the massive datasets of in-game user activities collected from Aion servers. Aion ranked as the world second-most played MMORPG with over 3.4 million subscribers from more than sixty countries as of early 2011 [?]. Our work is based on the real trace datasets, collected for three months from December 21, 2010 to March 21, 2011, which consists of all the activities of 94,497 users (in one of 44 Aion servers) like their communications, economic interactions, group behaviors, whose log size is around 918 GB.

To our knowledge, this measurement study is the first attempt to analyze groups' structural patterns, dynamics, and roles based on the seven most popular social interactions in Aion: Whispers (i.e., private messages), Friendship requests (i.e., adding a user to the buddy list of a player), Trades, Shops, Mails, Group chats, and Party invitations. In Aion, a user can join a *guild*¹ if she receives an invitation of a current member of the group. Also, she can move from one group to another. By being a member of a group, the user can check the status of other members by accessing the roster of the group, and can communicate with all of the other members simultaneously by using Group chats. To understand the implications of the above social activities in a group, we focus on: (i) how

¹We use a guild and a group interchangeably.

social interactions and economic behaviors within the group differ from the ones across users of different groups, (ii) what makes the number of members of a group rise, sustain, or fall, (iii) how and why group members join and leave a group, and (iv) what makes a group end.

We highlight the key findings of this paper as follows:

1. This is the first comprehensive study that analyzes the group activities of users in MMORPGs from a socio-economic point of view.
2. We classify the groups into three types in terms of vitality as follows: (i) a rising group, (ii) a stable group, and (iii) a falling group. We observe that rising groups (in terms of the number of members) exhibit more (i) cohesive social interactions, (ii) balanced communication patterns, (iii) skewed economic behaviors, and (iv) spatial and temporal correlation among group members, compared to the other groups.
3. We propose a *group network* whose vertex and edge indicate a group and the migration of users, respectively. We find that the group network exhibits a significant small-world property [?].
4. We show that broker groups (i.e., structural holes [?]) play important roles in the migration of users across groups, which demonstrates the brokerage theory [?].
5. We reveal that what social factors make members in group stay and leave the group. Our analysis can give an insight for stakeholders who are to encourage group activities such as social commerce events, social networking services, and MMORPGs.

We organize this paper as follows. After reviewing the related work in Section ??, we explain the key features of and social interactions in Aion in Section ??. Section 4 analyzes (i) how users interact with each other within a group and (ii) how social interactions are affected by group membership. Section 5 investigates what makes the number of members of a group rise, stable, or fall. After introducing a group network in Section 6, we investigate (i) how group members join and leave a group and why, and (ii) what makes a group end in Section 7. Finally we conclude the paper with future work in Section 8.

2. RELATED WORK

Social Interactions in MMORPGs: The landscape of user behavior studies like sociology or psychology has been fundamentally changed by the proliferation of online social networks [?, ?]. However, most of studies on online social networks have mostly focused on a single type of interactions (e.g., phones or online buddy relations), missing the wide variety of human interactions in real life [?, ?]. In contrast, MMORPGs provide rich virtual environments where users engage various real world-like interactions including combats, trades, and conversations with others, which allows researchers to explore the richer details of real-world-like complex and various social interactions [?, ?].

Consequently, there has been an increasing interest in social interactions in MMORPGs (e.g., virtual places for social purposes [?], shared experiences [?], and social bonds [?, ?]). However, most of the prior studies have used traditional methods of social science such as interviews and questionnaires that need substantial time and resources to deliver statistically meaningful assertions, which may also introduce well-known biases [?, ?]. Recently, [?] analyzed the structural equivalence among the interaction networks in

an MMORPG, and [?] investigated various kinds of social interactions (e.g., friendship, conversation, trade, and etc.) among users in an MMORPG, based on the datasets from game providers. Our work is also based on the datasets (and their analysis) of multiple social interactions of an MMORPG from game providers; however, we focus more on various social activities from a group perspective, which has been paid little attention.

Group Activities in MMORPGs: Understanding the group activities is important in human behavior studies due to the nature of people gathering together and forming groups, which is one of the key drives of a society [?]. Thus there have been a few studies to understand the motivation of group activities in MMORPGs, and the motivation of gaming or joining groups [?], based on the interviews or surveys [?, ?]. Also, some studies have tried to understand the structural properties [?] or stability [?, ?] of groups in MMORPGs. However they cannot see comprehensive interactions among users since their collected data is limited (i.e., querying the status of users only from the client-side interface provided in a game). [?] studied the combat groups (i.e., parties) in an MMORPG, which are formed for cooperative game play; however social aspects of groups are not investigated. To the best of our knowledge, this is the first work that comprehensively and empirically investigates the various group activities of users (i.e., social and economic aspects), using the records of users' activities provided by a game provider.

Group Activities in Other Online Services: Since gathering together and forming groups are the inherent structure of society, their structure and evolution have been investigated in other online services such as [?, ?, ?]. [?] tried to study the structures of *implicit* communities and their properties by identifying the clusters within a given graph, which are characterized by implicit factors such as the density of links. Also, there have been studies to investigate how the binary relationship (e.g., friendship or co-working relationship) affects the formation of *explicit* groups in LiveJournal [?], churning of users within a group (i.e., an identical conference) in DBLP [?], or network evolution in LiveJournal, Flickr, and YouTube [?]. In the context of social science, mathematical modeling (e.g., diffusion model) has been proposed to explain group evolution and change [?], but social interactions are not considered. We investigate the group activities in MMORPGs, where users can engage various real world-like interactions including conversations, trades, and combats.

3. AION OVERVIEW

In this section, we explain the key features of Aion from the perspective of social interactions, and introduce its datasets.

3.1 Game Features

Aion ranked as the second most played MMORPG with over 3.4 million people from more than 60 countries² as of early 2011 [?]. Similar to most of the other MMORPGs, a user chooses one of the virtual worlds to engage. In her world, she can do various kinds of social interactions with others including conversations, economic activities or joining a group much like in her real life.

3.1.1 Social Interactions

We model social interactions among users (in a world) as a graph $S = (V, E)$, where V is the set of users (or nodes) participating in the virtual world, $\{v_1, \dots, v_n\}$, and E is the set of directional social interactions, $\{e_1, \dots, e_m\}$, where $e_i \in \{\text{Friendship}, \text{Whisper}, \text{Mail}, \text{Group Chat}, \text{Trade}, \text{Shop}, \text{Party Request}\}$. A social in-

²<http://www.alteredgamer.com/pc-gaming/35992-mmo-subscriber-populations/>

teraction in Aion refers to one the following actions:

Friendship: A user can invite another user to be her *friend*. Upon the approval of the invited user, she can easily check the status of her friends. The direction of the edge is from the inviter to the invitee. There are 103,995 Friendship records in our datasets.

Conversation: There are three types of communications; *Whisper*, *Mail*, and *Group Chat*. A Whisper can take place between any two online users, and the others cannot overhear this. If the receiver is not online, the sender can send a mail. If a user belongs to a group, she can broadcast a message to all the other online members in the same group through a Group chat. For the three types of communications, we cannot see message contents; however, we can retrieve the sizes of the messages. There are 27,479,612, 49,706,934, and 475,236 records for Whisper, Group chat, and Mail, respectively.

Economic Activities: A user can send a request to another in proximity to exchange or give items using the *Trade* interaction. A user can also open a *Shop* in a designated place (in the virtual space), and any user can go to the *Shop* to purchase or sell in-game items. In this case, an outgoing edge (out-degree) is drawn from a buyer to a seller. Our datasets contain 407,783 Trade and 57,758 Shop records.

Party Requests: A user can send a Party request to anybody to accomplish a quest together. The user who receives the Party request can accept or reject. Note that a party consists of a few people (upto 6), usually to wage a battle.

3.1.2 Group Membership

In Aion, a user can join a guild (or a group), which is friendship based. For this, a member in a group invites her friends or someone who would like to join. A guild member can check the status of other members (of the same guild) by accessing the roster. A guild is a major element in the social life of online gaming communities [?], and has some similarities with a group in a real society [?]. Hence, the lifetime of a guild is relatively long, which often lasts for months, and the maximum number of members of a guild is 200. In this paper, we analyze a guild and the social interactions among the guild members. From our datasets, we identify 4,955 groups (or guilds) during the measurement period (30,690 and 19,995 users have joined and left the groups during the period, respectively).

3.2 Datasets

Aion uses a high-end log system that records every action of every user. We have retrieved all the user records of the *Tiamat* server, one of the 44 servers of Aion, for 91 days from December 21, 2010 to March 21, 2011. Our datasets include 94,497 (anonymized) users, 4,955 groups, 145 million social interactions. The total log size is around 918 GB. We remove the data of the bots from our datasets by using anti-bot scripts provided by NC-Soft. We also exclude the groups where the number of members is below three, which leaves us 3,177 groups. We focus on social interactions among users, user affiliation with groups, and user participation such as playtime.

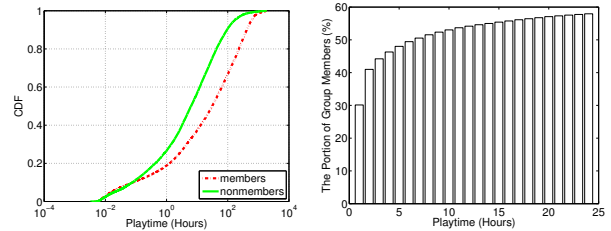
4. GROUP AFFILIATION

In this section, we investigate (1) how many users join groups, (2) how social interactions are affected by group membership, and (3) how users interact with each other within a group or across groups.

4.1 How prevalent are group activities in Aion?

In most of MMORPGs including Aion, a user can join no more than one group at any moment. In our datasets, 29,755 users (30%) among 94,497 users in Aion have ever joined groups. We have investigated 3,177 groups where the average number of users of a group is 8.70. The highest number of users of a group is recorded to be 148.

Figure ?? compares the playtimes of both (i) group members and (ii) nonmembers (i.e., users not belonging to any groups). As shown in Figure ??, group members play longer than nonmembers. Figure ?? plots the portion of group members as user's play time increase. We observe that users who play longer exhibit more group membership. Note that the portion of group members who have played longer than 10 hours (in 3 months) is higher than 50%. These results imply that group membership in MMORPGs may increase users' immersion/indulgence to play longer in a virtual world. This phenomenon is in line with the previous survey reports (e.g., [?, ?, ?]), which have claimed that a group membership is one of the important motivations for users to indulge in a game and to increase their playtimes by providing a social tie.



(a) Playtime distribution of group members vs. nonmembers (b) Portion of group members vs. user's playtime

Figure 1: As users spend more time in Aion, they are more likely to be group members.

4.2 Effect of Joining a Group

In most of MMORPGs including Aion, a user who wants to join a group should receive an invitation from a current member of the group. In this subsection, we focus on how the users' activities (e.g., communications or economic behaviors) are changed after they join groups. Figure ?? shows that communications and economic behaviors become more active after users join groups. We find that the number of private messages (i.e., Whispers) per user is marginally increased after users join groups. However, users having joined groups tend to send a large number of Group chats, which are broadcast only to group members. Thus, the volume of total messages (i.e., the sum of Whispers and Group chats) is increased by three orders of magnitude as compared with that of Whispers only. That is, users much more actively communicate with others by Group chats. We believe that the active communications within a group can be one of the main factors to increase the sense of group attachment, as reported in [?, ?, ?]. Interestingly, the average money of a user increases after she joins a group. This implies that the group membership may also encourage the economical activities in Aion.

4.3 Social Interactions Within a Group

We next investigate how users interact with one another within a group. To this end, we calculate the frequencies of social interactions occurring among users in the same group and those occurring among users across groups, respectively. Figure ?? shows that the social interactions of users are more active within a group. Note that most of the Friendship requests is two because a user who

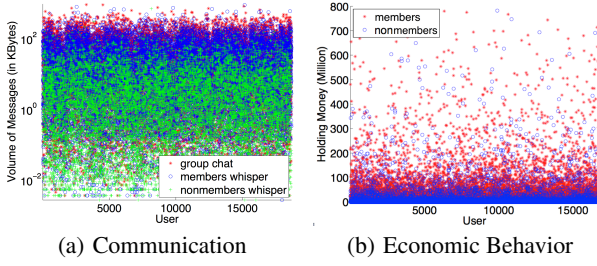


Figure 2: Users' activities (communications and economic behaviors) are boosted after they join groups. Note that the y-axis of the left graph is log scale.

sends a request typically receives a response. It turns out that the average number of Whispers between two members in the same group is 6.52 times larger than those between users across groups. Through this analysis, we conclude that social interactions occur more actively within a group in Aion.

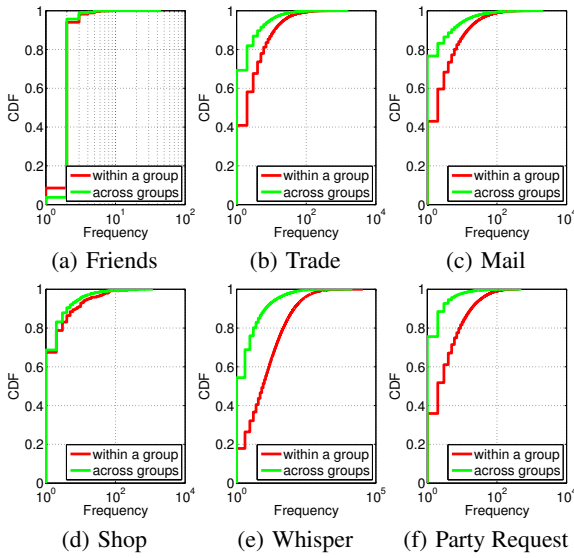


Figure 3: The frequencies of social interactions among members within the same group and those among users across groups are plotted, respectively.

We next investigate the structural patterns of social interactions happening in a group by computing (i) the clustering coefficient [?], and (ii) the reciprocity³. Figure ?? shows the average clustering coefficient and reciprocity of the six interaction networks in a group, which are compared with those of the interaction networks of the entire users. We find that the average clustering coefficient and reciprocity of most of the social interaction networks within a group are higher than those of the social interaction networks of the entire users, which indicates the structural patterns of social interactions within a group are more likely to be close-knit and reciprocal. We believe that this structural pattern of social interactions in a group is one of the most important factors to give users the sense of group attachment [?].

Interestingly, the clustering coefficient is the strongest in the Party Request interactions in a group. This implies that users in the same group are more likely to play a game together in a cohesive manner. In Figure ??, we also find that economical behaviors (i.e., Trade and Shop) are more reciprocal within a group, which means

³We define the reciprocity as the portion of bidirectional edges of a user to the total number of her edges.

not only communications and battle activities but also economical behaviors exhibit social characteristics (i.e., closely connected and reciprocal) more in a group. Note that the clustering coefficient of the Friend interaction network in a group is very close to that of the entire Friend interaction network. To our surprise, we find that only 4% of total Friendship requests take place among users in the same group. We conjecture that because a member of a group can easily check the status of other group members with a roster without making friends, she does not have to add other members in her friend list.

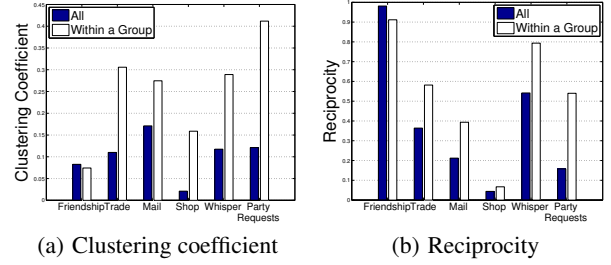


Figure 4: Average clustering coefficient and reciprocity of the six interaction networks for group members and for entire users are plotted, respectively.

5. GROUP DYNAMICS

There have been a few studies to show that one of the important factors of making a user join or leave an online community (i.e., LiveJournal or DBLP) is the relationship among group members [?, ?]. To see the phenomenon of user churning from a holistic viewpoint, we try to focus on how the number of members in a group is rising, falling, or stable. To this end, we classify the groups into three types in terms of vitality as follows: (i) a rising group where the number of its joining users is greater than 120% of that of its leaving users, (ii) a stable group where the number of its joining users is between 80% and 120% of that of its leaving users, and (iii) a falling group where the number of its joining users is less than 80% of that of its leaving users. It turns out that there are 1,498 rising groups, 754 stable groups, and 925 falling groups as shown in Table ?? . We investigate what factors (i.e., group cohesion [?], diversity [?], and spatial/temporal locality) affect the group vitality, depending on group types (i.e., rising, stable, and falling).

Type	# of members	# of joins	# of leaves
Rising	23.74 (23.98)	20.26 (20.14)	8.12 (10.38)
Stable	17.22 (20.95)	11.88 (14.18)	11.60 (13.36)
Falling	10.51 (11.31)	3.01 (4.89)	8.99 (9.85)

Table 1: Groups are classified into three types: Rising, Stable, and Falling. Averages (and standard deviations) of the numbers of members, joins, and leaves of three group types are shown, respectively.

5.1 Group Cohesion

Cohesion usually refers to the tendency of people to be in unity while working towards a common goal in a group [?]. Some studies have reported that users in a cohesive group have more satisfaction than the ones in a non-cohesive group [?]. To understand the cohesiveness of groups in Aion, we investigate the group cohesion from two perspectives: (i) the structural cohesion that focuses on the structural patterns of social interactions and (ii) the interaction scope that indicates whether social interactions take place between the members of the same group or not.

5.1.1 Structural Cohesion

In the literature, the cohesion can be measured in various ways [?]; we adopt the clustering coefficient [?] for this purpose in this paper. We further calculate the ratio of the clustering coefficient in the given interaction network to the one in a random network. To this end, we generate 100 random networks each having the same number of nodes and edges with the given interaction network and compute their clustering coefficients, which are averaged. Figures ??(a) and ??(b) show the clustering coefficient of each social interaction network and the ratio of the clustering coefficient in each social interaction network to the one in a random network, respectively. Since there are only three Shop interactions in the falling groups, we exclude them in this analysis. First, it is worth noting that the clustering coefficients of Friends and Shop networks are lower than those of the corresponding random networks as shown in Figure ?. We conjecture that (i) each member in the same group can easily check its member status, without adding their members into her friend list, which makes a lower clustering coefficient in all types of group networks as mentioned in Section 4.3, and (ii) members are exchanging their items or giving them without asking money (i.e., Trade) rather than selling them. We also find that the rising groups show the highest clustering coefficient across the five social interaction networks (except Friends) than other groups, which indicates that social interactions in the rising groups tend to be more clustered. Also, the falling groups show the lowest cohesion, which means members in the falling groups usually do not interact with one another actively. This observation is in line with the prior work [?], which reported that one of the common sources of dissatisfaction in a group results from the social distance.

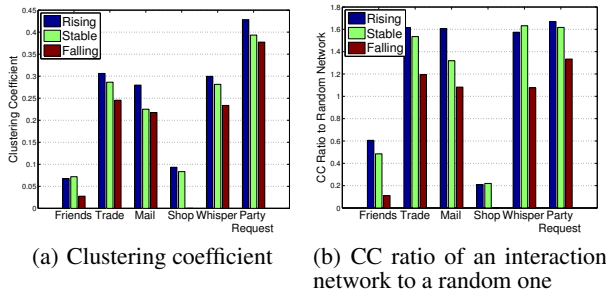


Figure 5: The clustering coefficients (CCs) and the CC ratio values of the interaction networks to random networks of rising and stable groups are higher than those of falling groups across all the interactions.

5.1.2 Interaction Scope

From the above analysis of the structural cohesion, we conclude that the interaction patterns of the rising groups are in contrast with those of the falling groups. We further investigate the interaction scopes of the social interactions by looking at whether social interactions happen within the same group or across groups. To this end, we compute how many social interactions occur (i) between members in the same group (i.e., intra-group) and (ii) between a member and a nonmember⁴ (i.e., cross-group). Figure ?? shows the ratio of the number of cross-group social interactions to the number of all the social interactions happening in the group. We find that rising groups have more intra-group social interactions than cross-group social interactions. Note that the rising groups have more intra-group social interactions than the stable or falling groups, which implies that the rising groups are more cohesive than the others. In

⁴Note that a nonmember means a member of another group or a user without any group membership.

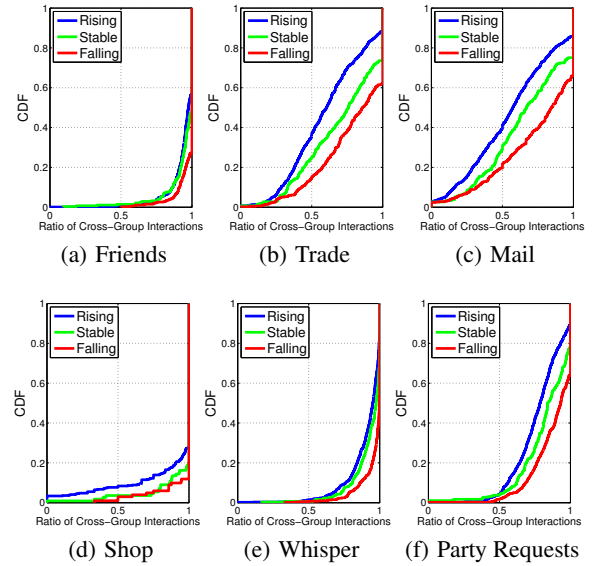


Figure 6: The ratio of the cross-group social interactions to all the social interactions happening in a group is plotted across the six interactions networks. Members in the falling groups tend to interact more with nonmembers. On the contrary, the rising groups have more intra-group social interactions than cross-group ones.

case of the Trade and Mail interactions, a half of their actions take place within the same group for the 40% of groups, which means the prevalence of intra-group interactions. However, in case of the Friendship interactions, even though the rising groups have more intra-group social interactions than the others, we find that most of their Friendship requests are made towards non-members, which is in line with the results of the clustering coefficient in Section ?.

5.2 Group Diversity

In this subsection, we investigate how the social interactions, communications, and economical behaviors exhibit diversity depending on the group's vitality (i.e., rising, stable, and falling).

5.2.1 Social Interaction Diversity

Prior studies [?, ?, ?] suggested that one of the motivations to join a group is the social interactions taking place in the group. To examine how diverse social interactions affect the group vitality, we quantify the diversity of social interactions within a group by calculating the Shannon diversity index (or entropy) defined by:

$$H' = - \sum_{i=1}^A p_i \ln p_i \quad (1)$$

where A is the number of interaction types and p_i is the relative proportion of the i^{th} interaction type among total interactions in a group. Figure ?? shows the CDF of the entropy of the social interaction diversity. As shown in Figure ??, rising groups have the higher entropy, which signifies the balanced social interactions among the members. In other words, groups whose social interaction types have strong disparity may tend to not grow further.

5.2.2 Communication Diversity

We next consider the communication diversity (e.g., whether and how each member has a fair chance to talk in a group.), which may be crucial for group members to mingle. For example, if some members monopolize Group chats, this may make some members

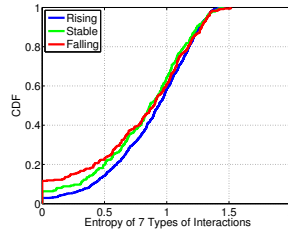


Figure 7: Rising groups exhibit balanced social interactions than other groups. alienated. We conjecture that the monopolized communications can be a reason to make some members leave the group.

We estimate how users evenly communicate with each other within a group by using the Shannon’s entropy. Figure ?? shows the normalized entropy of the Group chats in a group. Note that since every group has a different number of the members, the entropy of Group chats is divided by the maximum entropy, $\log_e M$ where M is the number of members in a group, for normalization purposes. As shown in Figure ??, members in rising groups communicate with other members in the same group more evenly than the other groups. [?, ?] showed that one of the motivations to join a group is to chat with various kinds of people. In this sense, it seems that a balanced communication pattern could lead people to stay in the group and to invite more users into the group.

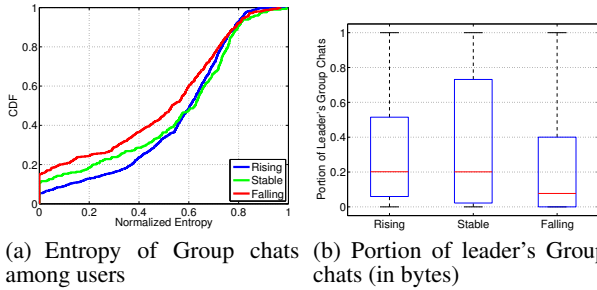


Figure 8: Members in rising groups communicate with other members more evenly than the ones in other groups. The portions of leaders’ Group chats in stable groups are significant.

In earlier work [?, ?], it is pointed out that the role of a leader in a group is critical to keep the community/group alive. For example, one of the reasons for a group to come to an end is a poor leadership of the group. We notice that many of the notifications from a leader are often conveyed through Group chats in Aion. If the portion of the leader’s Group chats is high, the leadership may be deemed active in the group. Thus we calculate the portion of the leader’s Group chats in each group in Figure ?? using boxplots (the red bar is the median). To our surprise, we find that leaders in 40% of the falling groups do not have any conversations in a group, which means the indifference of the leaders. In contrast, in the stable groups, the average value of the portion of the leader’s Group chats is 37%, which implies the leaders’ activeness while rising and falling groups have 32% and 26% respectively. From Figures ?? and ??, we find that the low entropy (skewed patterns of dialogues) of the stable groups is mainly caused by the leaders.

5.2.3 Economical Diversity

One of the key factors of the virtual world attracting millions of users is virtual money in game. By using the in-game money, users can decorate their avatars or buy virtual goods (e.g., weapons and armors) to increase their power and reputation in the virtual world. To understand the economical behaviors of users in groups, we consider not only the amount of the in-game money that indi-

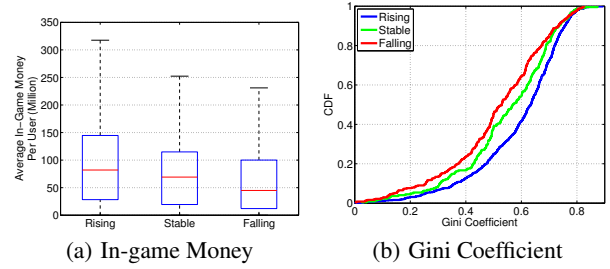


Figure 9: Rising groups tend to have more in-game money than other groups. However, economical behaviors are skewed in rising groups.

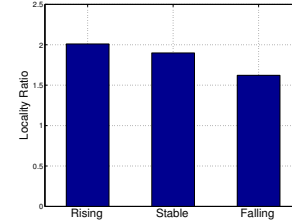


Figure 10: The locality ratio of a real group to a uniform hypothetical one is plotted for each group type. Falling groups show the least spatial locality.

vidual users have, but also the economical diversity which indicates how the fortune of a group is evenly distributed in the group. To this end, we calculate (i) the average in-game money among users in a group, and (ii) *Gini coefficient* which is a well-known estimator to evaluate the disparity of a distribution in economics [?]. The Gini coefficient is always within the range of $[0, 1]$, where 0 means a perfect uniform distribution and 1 means an extremely skewed distribution [?]. As shown in Figure ??, we find that rising groups have more in-game money than other groups, which indicates that economical activities are more active in the rising groups. However, economical behaviors are significantly skewed in the rising groups. Interestingly, more than 82% of the rising groups, 80% of the stable groups, and 71% of the falling groups exhibit greater Gini coefficients than 0.4. This implies that the whole fortune of a group is skewed to a small portion of users within a group, which will be detailed in Section 7.

5.3 Group Locality

In this subsection, we investigate how group members are physically closely located in real world or play at similar timeframes depending on the group’s vitality (i.e., rising, stable, and falling).

5.3.1 Spatial Perspective

To investigate whether (online) group members are located in close (offline) real-world locations, we estimate each user’s location by using WHOIS API⁵ which is provided by KISA (Korea Internet Security Agency) who manages all the IP addresses in Korea. Based on the location information of each user in a group, we calculate the *spatial locality*, which is defined as the probability that randomly-selected two members (in the same group) have the same locale [?]. Note that we deem that the members have the same locale if they belong to the same city and borough. We assume that physical proximity among (online) members implies a certain degree of spatial correlation.

⁵<http://whois.kisa.or.kr>. This service provides high accuracy since it is managed by Korean government in cooperation with Internet Service Providers (ISPs) in Korea.

To verify if the spatial locality exists, we calculate the locality values of hypothetical groups (with the same numbers of members) whose members are uniformly distributed among all locales. Figure ?? plots the average locality of real groups in our datasets divided by that of hypothetical ones depending on the group’s vitality. If the calculated value in Figure ?? is higher than 1, we can say there is a spatial locality in the group. We observe that the spatial locality of groups is higher than that of hypothetical ones, which indicates that members in the same group are likely to be located in similar places in real world. Interestingly, we find that the locality ratio of the rising groups is larger than that of the other groups. This implies that offline closeness (i.e., spatially correlated distribution of members) exists in growing groups whose social and economical activities are more active than other groups, which may support the claim that offline bonding can be a factor to be members of the same group [?].

5.3.2 Temporal Perspective

We next investigate how group members play games at similar timeframes (i.e., temporal locality of each group). To this end, we calculate two metrics to estimate the temporal locality: (i) the overlapping time (duration) among members of the same group, and (ii) the degree of simultaneous engagement among group members. The first metric is proposed in [?], which can be used to validate that concurrently playing with other members is often mentioned (by users) as an important reason not to leave the group [?]. We estimate the average overlapping time by calculating each member’s login and logout times in Figure ???. However, from the first metric, it is hard to say whether group members actually have played together. To check the simultaneous play among group members, we focus on a party. A party is formed for a relatively short interval to accomplish a quest (i.e., mostly battles) together by a few users. Note that any users (regardless of group membership) can constitute a party. In Figure ??, we plot how many parties have been formulated only by members in the same group and how long a group member has participated in parties (that each consist of the same group members) during the measurement period. Note that the overlapping and party-participating times of a user in a group are normalized by its group size, respectively.

As shown in Figure ??, stable and falling groups exhibit the lower overlapping time together than rising groups. Note that falling groups also show the smaller number of parties and the shorter party-participating time than other groups. This means that even though falling group members are staying together in game, they barely play together, which is in line with the results showing the lower cohesion of groups in Figures ?? and ??. Meanwhile, stable groups exhibit comparable party-participating time to rising groups, which indicates that members in stable groups are likely to play the game together when they stay online.

In summary, members in rising groups are more spatially and temporally correlated among group members than members of other group types. This implies that not only social or economical behaviors among users in the virtual world, but also the location and time in the real world are important factors for group vitality.

5.4 Survival Rate

We next investigate how many groups (in our datasets collected in 2010 and 2011) are currently alive (as of Aug. 2013) and active, which is 32 months after from our measurement period. To this end, we have collected current status (e.g., current number of members or leader’s name) of groups from the Aion website⁶. We query the corresponding group information to the website by its name and

⁶<http://search.plaync.co.kr/aion/>

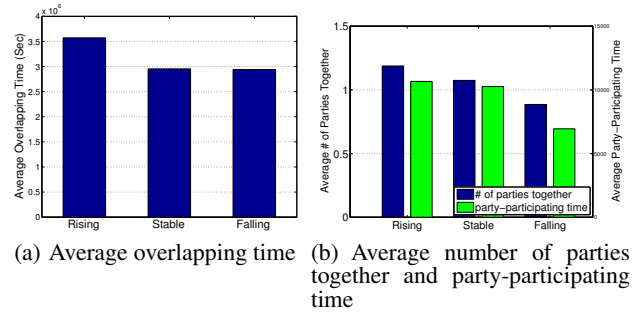


Figure 11: Rising groups show the highest overlapping time, number of parties together and party-participating time.

creation time. If the queried group information is not available, we conclude it has ended.

Table ?? summarizes the average number of members and group’s survival rate depending on the group’s vitality. To our surprise, we observe that 34.1% (1,084 / 3,177) of groups are still alive and active. Note that rising and falling groups still have the largest and smallest number of members even after 32 months have passed, respectively. This signifies that the group vitality does not show substantial changes as time goes on. Interestingly, the survival rate of stable groups is even lower than that of falling groups, which will be detailed in next subsection. Also we will further analyze which factors (i.e., group’s cohesion and diversity) affect their survival rate in Section 7.

Type	Average # of members	# of survived groups	Survival Rate
Rising	14.07	567	37.9%
Stable	12.06	199	26.4%
Falling	8.89	318	34.4%

Table 2: Average number of group members, number of survived groups, and group’s survival rate are shown depending on the group’s vitality.

5.5 Dichotomy in Stable Groups

We notice that stable groups, whose rates of joining and leaving users are similar, can be divided into two sub-types: (i) groups where most of joining users are leaving soon within the measurement period and (ii) groups where most of joining users staying during the measurement period. The former type indicates that joining users (i.e., newcomers) of the group cannot mingle with old members, which leads the newcomers to leave soon. In contrast, the latter case means that newcomers usually stay for a while.

To quantitatively differentiate the two sub-types of stable groups, we first introduce a new metric *overlapping ratio*, which is defined as the number of users in the intersection of the joining and leaving users divided by the number of the users in the union of them. That is, if the overlapping ratio of a group is high, users who have joined the group are likely to leave soon. We compare the overlapping ratio among three group types (rising, stable, and falling) in Figure ???. As shown in Figure ??, the overlapping ratio of the half of stable groups is over the 0.5, which means more than a significant portion of newcomers leave in a short time. To investigate these groups, we quantitatively classify stable groups into two sub-types based on the overlapping ratio: (i) groups having high overlapping ratio (> 0.5 , *stable-high*) and (ii) groups having low overlapping ratio (≤ 0.5 , *stable-low*). Figure ?? compares the *stable-high* groups and the *stable-low* groups in terms of group cohesion, diversity, spatial/temporal locality, and survival rate. As shown in Figures ??

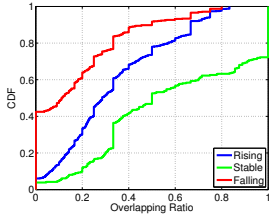


Figure 12: Overlapping ratio depending on group vitality is plotted.

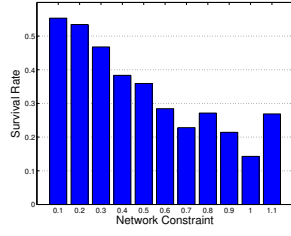


Figure 13: As the network constraint of a group becomes higher, its survival rate is decreased.

and ??, we observe that the *stable-low* groups exhibit the higher clustering coefficient and Group chat entropy than the *stable-high* groups. This implies that stable groups whose newcomers stay longer have stronger cohesion and more fair participation in conversations. The difference between two sub-types of stable groups is remarkable at their survival rates. Surprisingly we observe that the survival rate of the *stable-low* groups is 2.15 times higher than that of the *stable-high* groups as shown in Figure ??. We conjecture that frequent user churning may affect the survival rate eventually. From the spatial and temporal perspectives, we similarly observe that the *stable-low* groups have higher spatial/temporal locality than the *stable-high* groups. This implies that members in the stable groups whose members are spatially/temporally localized are likely to stay longer.

6. GROUP NETWORK

So far, we have investigated various activities which occur within a group mostly. We now turn our attention to the relations among groups or user migration across groups. To this end, we propose a *group network* whose vertex is a group and edge is a relation between two groups. We assume that there is a relation between two groups A and B if there are users who move from group A to group B. More specifically, we define a group network G as a directed weighted graph $G = (V, E, W)$, where V is the set of groups, E is the set of directional edges for migration of users, and W is the number of users having migrated between the two groups. That is, if a user moves from group 1 to group 2, there is an outgoing edge from group 1 (or vertex 1) to group 2 (or vertex 2).

6.1 Properties of the Group Network

There have been many studies that investigate structural properties of online social networks (OSNs) [?, ?, ?, ?]. Here, we focus on the set of groups (instead of the set of individual users), which are under-appreciated by the research community. Thus, we build the group network to look at the dynamics at group level, while other OSNs are for user level dynamics. That is, an edge between two users in an OSN is usually based on user's relationship (e.g., friendship, follower/follower and so on) while an edge from group A to group B in the group network is set up if a user moves from group A to group B. We believe that investigating the structural properties of a group network is important for understanding how people move across groups and what groups play more important roles in the migration of people across groups.

Table ?? summarizes the structural properties of the group network in Aion, along with those of well-known OSNs (Facebook, Flickr, and Cyworld [?, ?, ?]) for comparison purposes. When we compare the group network with the other OSNs, we find that the average degree of the group network is substantially lower than the

	# of nodes (edges)	Average degree	CC	Path length
Aion Group	4,022 (17,033)	4.24	0.40	2.26
Facebook	63,730 (817,090)	25.7	0.22	NA
Flickr	2,302,924 (23,838,276)	20.9	0.18	NA
Cyworld	11,537,961 (177,566,730)	30.9	0.16	NA

Table 3: The main characteristics of the group network in Aion, along with online social networks (Facebook, Flickr, and Cyworld) are presented for comparison purposes.

others. Interestingly, even though the average degree is low, we observe that the clustering coefficient of the group network is substantially high (0.40) compared with those of OSNs. To compare the clustering coefficient (CC) of the group network with those of random networks, we generate 100 random networks based on the Erdős & Rényi (ER) model [?] while preserving the same numbers of nodes and edges. As a result, the average and standard deviation of the CC in random networks are 0.0021 and 0.0002, respectively. We notice that the CC of the group network is significantly higher (190 times) than that of the random network while its average path length is quite small (2.26), which signifies the *small-world* property of the group network. To quantify the 'small-worldness' [?] of the group network in Aion, we calculate the small-world index σ_{SW} , which is defined as:

$$\sigma_{SW} = \frac{\gamma/\gamma_{random}}{\lambda/\lambda_{random}} \quad (2)$$

where γ and λ are the CC and the path length of the given group network, respectively, and γ_{random} and λ_{random} are the clustering coefficient and the path length of the random network with the same numbers of nodes and edges as the given network, respectively. If σ_{SW} is greater than one, it means that the given group network has the small-world property [?]. We find that the average and standard deviation of σ_{SW} is 343.56 and 33.96 respectively, which reveals the substantial small-worldness of the group network. It is interesting that the small-world property is found not only at the level of users [?, ?], but also at the level of groups.

6.2 Structural Holes

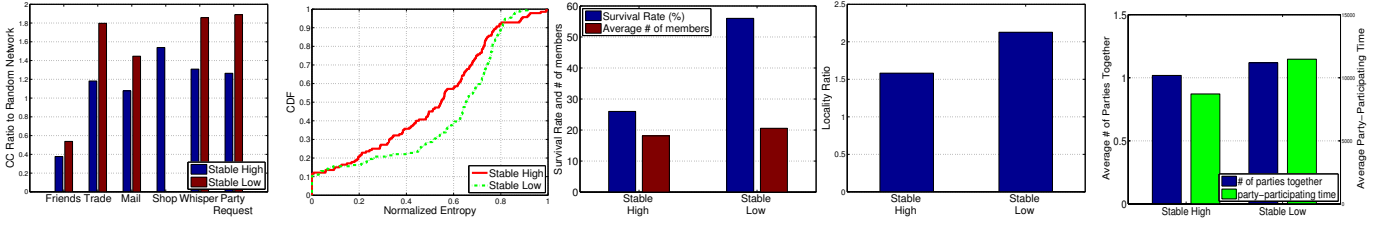
In sociology, a *structural hole* [?] in a given network is defined as a bridging edge that connects two denser sub-networks, which is similar to the weak tie in Mark Granovetter's theory [?]. The structural holes are often strategically important from social and economical perspectives [?, ?]. However, the presence of structural holes in a group network and their characteristics remain unexplored so far.

To find the structural holes in the group network, we first compute the network constraint of every node using Burt's formulation [?]. The network constraint of a group i is defined as:

$$C_i = \sum_j (p_{ij} + \sum_q p_{iq} p_{qj})^2, \quad q \neq i, j \quad (3)$$

where $p_{ij} = z_{ij} / \sum_q z_{iq}$. In our case, z_{ij} is the number of users who move from group i to j . The smaller network constraint a vertex has, the more likely it is connected to a structural hole (i.e., broker).

Table ?? shows the Pearson's correlation coefficient between the network constraint and group activities (i.e., economical behaviors and user dynamics). We first find that the network constraint and the diversity of the social interactions are negatively correlated ($\rho = -0.2217$), which indicates that the groups which are more of structural holes tend to have diverse social interactions. This result is in line with [?], which found that users who tweet diverse topics are likely to be the structural holes. Also, the correlation



(a) CC ratio of an interac-
tion network to a random among users
one

(b) Entropy of Group chats

(c) Survival Rate

(d) Spatial locality

(e) Temporal locality

Figure 14: *Stable-low* groups show the higher clustering coefficient and communication diversity than *stable-high* groups. Member churning (and hence the survival rate) is highly related with its entropy of Group chats and spatial/temporal locality.

Network Constraint	User Dynamics			Outgo		Fortune/Money	
	Interaction Diversity	# of joins	# of leaves	Group	Per member	Group	Per member
	-0.2217	-0.5494	-0.5231	-0.3288	-0.1264	-0.448	-0.1442

Table 4: Correlation coefficient ρ between network constraint and (i) user dynamics, (ii) outgo, and (iii) fortune/money are shown, respectively. All values are statistically significant (p -value < 0.01).

between the network constraint and the number of joins/leaves is significantly negative, which means many users migrate through the groups corresponding to the structural holes. Interestingly, the groups of structural holes seem to be successful from an economical perspective; they have more fortune than other groups. This result is consistent with [?], which showed that structural holes boost the firm performance in fund companies.

We finally investigate whether the brokerage theory holds in the longevity of groups. Thus we calculate each group's survival rate depending on their network constraints. As shown in Figure ??, to our surprise, the survival rate of a group decreases as its networking constraint increases. Hence, we conclude that the brokerage groups are likely to survive longer than other groups.

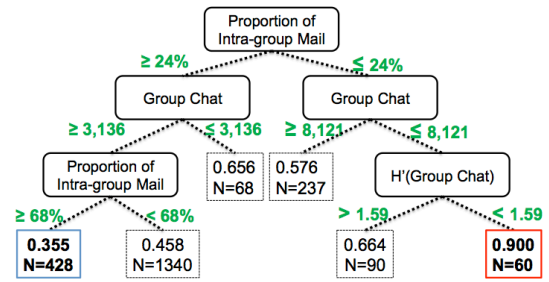
In summary, we observe the phenomena of the structural hole theory [?]; that is, a weak-tie (i.e., structural hole) can lead to social and economical success by providing access to diverse sources of expertise (i.e., people). By applying the metrics of the brokerage theory into the groups in Aion, we reveal that the brokerage theory holds at the level of groups.

7. IMPLICATIONS

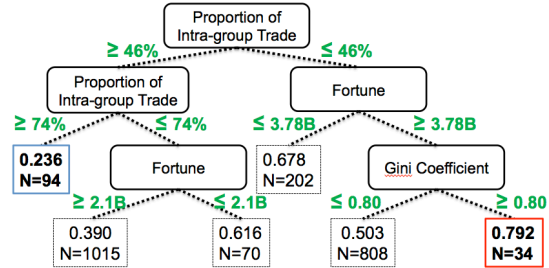
In this section, we seek to answer the following questions: (i) what factors make people leave a group? and hence (ii) what makes a group end? To answer the above questions, we adopt a well-known machine learning technique by leveraging the RPART (Recursive PARTitioning and Regression Tree) package [?] in the statistical program *R* to train and test a classifier. Note that we set 70% of the 3,177 groups for a training set and the other 30% for a test set in the training and testing phases of a classifier (which consists of multiple features).

7.1 Why people leave groups?

There have been many studies to understand the churning behavior of a user from a group to another for many purposes (e.g., increasing sales in economics [?] or system performances in peer-to-peer networking [?]). In particular, social studies have found that the number of friends is crucial for users to join/leave a group [?, ?], but the diverse aspects of social interactions have not been thoroughly investigated. In this subsection, we seek to understand what factors play a key role in making people leave groups. We investigate the churning behaviors from two perspectives: (i) communication patterns and (ii) economical behaviors. We believe understanding the churning behaviors of people with empirically-grounded ev-



(a) Communication patterns



(b) Economic behaviors

Figure 15: Top three levels of the decision trees as to communications patterns and economic behaviors are illustrated. The average churning rate is 0.47. N is the number of groups for each classification criterion. Note that root node errors of the decision trees for the communication patterns and economical behaviors are 7.5% and 6.6%, respectively.

idences is important for stakeholders who are to encourage group activities such as social commerce events, social networking services, and MMORPGs.

7.1.1 Classifier Formulation

We classify the various social interactions in a group into two categories: (i) communication patterns and (ii) economical behaviors. Table ?? summarizes the features in the first two categories that we use in this analysis.

Feature Categories	Features
Features related to communications within a group	Ratio of numbers of (i) Friendship requests, (ii) Mails, and (iii) Whispers within a group to the ones across groups Number and Entropy of Group chats (frequency & bytes) Clustering coefficient and Reciprocity of (i) Friendship request, (ii) Mails, and (iii) Whispers Ratio of number of leader's Group chats to that of entire members (frequency & bytes)
Features related to economical behaviors within a group	Ratio of income to outgo of a group Fortune (Sum of in-game money of group members) & Gini Coefficient Ratio of numbers of (i) Trades and (ii) Shops within a group to the ones across groups Clustering coefficient and Reciprocity of (i) Trade and (ii) Shops
Features related to the survival rate of a group	Overlapping ratio Spatial locality Average staying time with group members Average number of parties consisting of group members Average party-participating time with group members

Table 5: Features in group characteristics selected for machine learning are listed.

7.1.2 Results and Discussions

Figures ?? and ?? show the top three levels of the two classifiers made up of the features of the communication patterns and economical behaviors, respectively. Here, N is the number of groups that are classified according to the classifier tree. The communication-based classifier to characterize groups with high and low churning rates tells us that: (1) if the portion of the number of Mails sent outside the group is relatively high ($> 24\%$), (2) if the number of Group chats is not high ($< 8,121$), (3) if the Group chats are skewed to a small number of members (i.e., low entropy), the churning rate is the highest (0.900). Note that if the portion of the Mails inside the group is high ($> 68\%$) and the number of Group chats is not low ($> 3,136$), the churning rate exhibits the lowest.

The economical behavior-based classifier reveals that the high portion of the Trade interactions inside the group ($> 74\%$) makes the churning rate the smallest. To our surprise, however, even with the large fortune of the group (> 3.78 billion), if the distribution of the money is biased (Gini coefficient > 0.8), the group's churning rate is the highest. In summary, these results indicate that the communication patterns and economical interactions in a group are critical for users to stay or leave the group, which complements [?, ?] that have not considered various social interactions.

7.2 Why a group ends?

In this subsection, we seek to understand what factors play a key role in making a group end.

7.2.1 Classifier Formulation

In addition to the features used in the previous subsection, we additionally consider various group properties such as group's spatial/temporal locality and overlapping ratio, which are detailed in Table ?. Note that the features in the last category in Table ? are collectively used for constructing the decision tree in this analysis.

7.2.2 Results and Discussions

Figure ?? shows the top two levels of the classifier made up of all the features in Table ?. Interestingly, despite setting the maximum depth of the tree 15 in the partitioning algorithm in RPART, the final tree exhibits only two levels (the average staying time together in the game and the overlapping ratio), which means the two classification criteria are critical for the group's survival rate. We first find that if the average staying time along with members in a group is low (< 150 hours), the survival rate exhibits the lowest (13%), which indicates that simultaneous playing with the group members is crucial for the group's survival. We also observe that (1) if the group's average staying time in the game is high (≥ 150 hours) and (2) if the overlapping ratio is low ($< 48.4\%$), the survival rate is the highest (50%). This implies that groups where members stay together in the game and newcomers mingle with old members are likely to sustain.

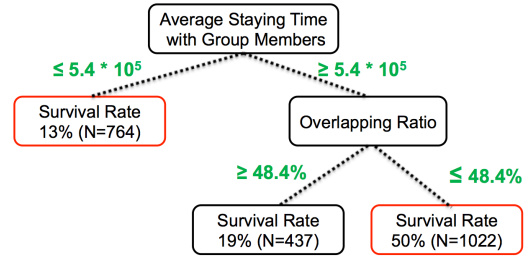


Figure 16: Decision tree for a group survival rate is constructed. N is the number of groups for each classification criterion. Root note error is 21.3%.

8. CONCLUSIONS

We have comprehensively analyzed the group characteristics in Aion from a socio-economic point of view. Our analysis revealed that structural patterns of social interactions within a group are more likely to be close-knit and reciprocal than those across groups. We also showed that rising groups in terms of number of members exhibit more/higher (i) cohesive social interactions, (ii) balanced communication patterns, (iii) skewed economic behaviors, and (iv) spatial and temporal correlation among group members, compared to the other groups. Based on the machine learning analysis, we revealed interesting findings for group characteristics: (1) if a group is not cohesive, not actively communicating, or not evenly communicating among members, members of the group tend to leave, and (2) if a group's members stay together in the game and its newcomers mingle with old members, it exhibits the high survival rate. Our ongoing work includes investigating (i) the structural patterns of economic behaviors in virtual worlds and how they affect the group activities and social interactions, and (ii) the differences between real-world groups and virtual-world groups from a socio-economic point of view.

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