Unveiling a Socio-Economic System in a Virtual World: A Case Study of an MMORPG

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ABSTRACT

Understanding socio-economic systems in MMORPGs can provide an important implication on how people participate in the economy and how people interact with each other. In this paper, we model the socio-economic system of an Aion, a popular MMORPG, as a multi-layer graph. Using the dataset consisting of 94,870 users and their activity records spanning three months, we examine how economic activities are associated with social interactions, and find that social interactions like participating in a party or exchanging messages are highly correlated with the trade activities. We also find that virtual economy in Aion is heavily inclined to a small number of *upper-class users* who play a crucial role in virtual economy. Our analysis on the upper-class users reveals that a significant portion of them reach at the max-level and tend to either (i) have many social interactions with others or (ii) play extremely much time with no social activity. We also reveal that there are some low-level upper-class users who gain much money but hardly socialize with others. Lastly, we show how upper-class users who are at low-levels, play the game extremely much more than others, or rarely interact with other users, are associated with the Real Money Trade (RMT), which may be an illegal behavior that gathers in-game money for exchanging into real-world money. We reveal that more than half of total money exchanged through the trade are associated with the upper-class users who involve in the RMT.

KEYWORDS

MMORPG; Real Money Trade; Aion; Socio-Economic Analysis

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1 INTRODUCTION

Over the last decade, online games have become very popular, and one of the popular genres is Massively Multi-player Online Role-Playing Games (MMORPGs). It has been reported that there are more than millions of users enjoying MMORPGs [30]. An MMORPG provides a *virtual world* where players can participate in not only game-specific activities but also various social interactions such as making friends, talking, or forming groups. Moreover, an MMORPG often has its own economy system where players can buy, sell, or trade virtual money or items.

Such a realistic virtual world of an MMORPG can provide an opportunity for researchers to study in-depth patterns and dynamics of complex human behaviors. In other words, a virtual space of an MMORPG can be viewed as a large virtual laboratory where researchers can observe diverse human behaviors easier than real world. This in turn has attracted many researchers to study human behaviors and social interactions revealed in MMORPGs [5, 8, 9, 15, 19, 28, 32, 33]. Also, security issues in MMORPGs such as illegal real money trade [10, 22, 23, 34] and bot detections [11, 12, 18, 20, 24] have been extensively investigated. However, most of these studies paid little attention to understanding how a virtual economy (revealed in an MMORPG) is associated with user behaviors and social interactions among users. Modeling and understanding a virtual economy can shed light on how people participate in the economy and how people interact with each other.

We aim at modeling and analyzing the socio-economic system in Aion, a popular MMORPG run by NCsoft. We perform an in-depth analysis on the large-scale dataset that consists of 94,870 users and their economic and social activity records spanning three months from December 21, 2010 to March 21, 2011. In particular, we model the socio-economic system of Aion as a multi-layer graph that consists of two economic-related graphs (trading items among users and buying/selling items over the agency) and three social interaction graphs (exchanging messages, participating in a party, and making friends). Based on the constructed graphs, we examine how economic activities are associated with social interactions, e.g., whether two users who participate in a party also trade items or money. We then identify the *upper-class users* who play a crucial role in economic graphs in Aion. We characterize the upper-class users in terms of in-game traits, as well as patterns of social and economic activities.

Among the upper-class users, we explore the suspicious ones who show distinct or even abnormal patterns compared to normal upper-class users. In particular, we investigate how the suspicious

upper-class users who are at low levels, play the game much more than others, or rarely interact with others, are associated with the Real Money Trade (RMT), which is known as an illegal behavior that gathers in-game money in exchange for real-world money [22]. We examine how such suspicious upper-class users affect the virtual economy of Aion.

We highlight the key findings of this paper as follows.

- **Modeling and analyzing a multi-layer graph that reflects social and economic activities:** By modeling and analyzing the multi-layer graph that represents the socio-economic system of Aion, we show that all the social and economic graphs follow the power-law distributions. Our analysis further reveals that social interactions like participating in a party or exchanging messages are highly correlated with the trade activities. For example, if two users participate in the same party, they are likely to trade items (or money) since the members of the same party are likely to trade items to distribute rewards after completing tasks such as achieving quests or killing monsters.
- **Characterizing the upper-class users:** We show that virtual economy in Aion is heavily inclined to a small number of users who play crucial roles in economic graphs. Our analysis reveals the upper-class users (from an economic perspective) exhibit distinct in-game traits and socio-economic activity patterns. A significant portion of the upper-class users reach the max-level in Aion and tend to either actively participate in social activities or play extremely much time (e.g., 15 hours or more a day) with no social activity. We also reveal that there are some low-level upper-class users who gain much money but hardly socialize with others.
- **Understanding the upper-class users associated with real money trade (RMT):** We show how suspicious upper-class users are associated with the RMT. We identify 470 gold farmers who mostly focus on collecting virtual money by repeatedly conducting in-game activities such as hunting monsters, and 382 money launderers who receive in-game money from gold farmers (through the trade) and exchange the received virtual money into real-world money, among the 2,371 upper-class users. Our analysis reveals that at least more than half of total money exchanged through the trade are associated with those gold farmers and money launderers who involve in the RMT, implying that such misbehaving users in the upper-class substantially affect the virtual economy in Aion.

2 RELATED WORK

As MMORPGs have become very popular as a large virtual laboratory where researchers can observe diverse human interactions, many researchers have studied human behaviors and social interactions using the datasets of MMORPGs. Lou *et al.* found gender swapping phenomenon where users change their actual genders in a virtual world [28]. In [17], the authors investigated item trading patterns and found that there are generous users who give virtual goods to help others without any return, and the altruism is even spread across users. Ducheneaut *et al.* explored the social activities of users and their locations, and found that users tend

to show different social activities depending on the properties of spaces [8]. As one of the social activities, some researchers have investigated group activities in MMORPGs [5, 9, 15, 19]. Ducheneaut *et al.* studied what factors are associated with the group persistence in MMORPGs [9]. Chung *et al.* analyzed social and economic behaviors among group members, and showed that cohesive social interactions and balanced communication patterns are key factors to maintain affiliations in an MMORPG [5]. Johnson *et al.* investigated behavioral differences between groups in MMORPGs and gangs in real world [15]. Some researchers have analyzed user behaviors from an economic perspective [4, 25, 26]. In [25], authors investigated the applicability of theory in economics to virtual world. Castronova *et al.* [4] and Vili *et al.* [26] found that users' economic behaviors such as purchasing, selling, or trading in virtual world are similar to the ones in real world.

In MMORPGs, virtual goods can be purchased through money in real world, called the *real money trade* (or gold farming). Since it is prohibited in most MMORPGs in general, there have been many studies to characterize and detect the real money trade [10, 22, 23, 34]. Kwon *et al.* investigated in-game trade networks in an MMORPG, and characterized the structure of the real money trades and their participating entities. Fujita *et al.* also analyzed the real money trades in another MMORPG by exploring the trade network and the volume of trades by users. Also, since gold farming are known as tightly coupled with bots, there have been studies for detecting such bots [1, 11, 12]. Ahmad *et al.* investigated *gold farming groups* whose members use illegal (bot) programs to mine virtual goods for real money trades [1]. Golle *et al.* proposed a CAPTCHA-based method to detect bot programs [12] while Gianvecchio *et al.* exploit the patterns of keyboard or mouse inputs [11]. There also have been other approaches using the characteristics of users' in-game behaviors [18, 20, 24].

The prior studies have revealed valuable insights into understanding not only behavioral characteristics of social or economic activities in MMORPGs, but also illegal economic patterns observed in real money trading. However, relatively little attention has been paid to understanding how virtual economy in MMORPGs are associated with social behaviors, how the upper-class users who play crucial roles in virtual economy show the distinctive characteristics in terms of in-game traits and socio-economic behaviors.

3 OVERVIEW OF AION

In this section, we introduce how users behave in Aion. We then describe our dataset used in this paper.

3.1 Activities in Aion

Aion was the second largest MMORPG as of 2011. It was reported that more than 3.4 M people in around 60 countries played Aion as of 2011 [13, 14]. A user in Aion can choose one of the virtual worlds to be engaged in, and create an *avatar* (or character) that may reflect his/her identity. In the virtual world, a user makes effort for raising his/her character(s) by hunting monsters alone or with other users as a group. In addition, a user can trade items with others or send money to others as economic activities. Also, as social activities, a user can communicate with others through

individual or group messaging channels. We now describe economic and social activities appeared in Aion in the following.

3.1.1 Economic activities. In Aion, a user can send and receive items or game money through the following channels.

- **Agency:** Aion provides an agency system where users can sell or buy item(s). To sell an item, a user visits one of the pre-defined and distributed spots (of the agency) in the virtual world and registers the item with the agency at its price. A buyer who visits the spot can buy the item. The agency deducts around 2% of the item price as a commission fee, and pays back to the sellers. Note that a user is allowed to use the agency only after his/her level reaches 9 in Aion.
- **Trade:** Two users can directly barter items or money, which is called as a 'trade' in Aion.
- **NPC shop:** Aion provides a shop operated by a non-player character (NPC) who is called as 'merchant'. In an NPC shop, items are mostly sold with fixed prices. Users tend to sell less valuable items at an NPC shop.
- **Mail:** Users can send mails with items or money as attachments in Aion. Since most of the mails in Aion contain items or money as attachments (89.4%), exchanging mails can be regarded as an economic activity rather than a social activity.
- **User shop:** A user can open a shop operated by herself to sell items. Unlike the agency, a seller does not have to pay fees for item deals. To buy an item in a user shop, a buyer needs to visit the seller's shop whose location is fixed.

3.1.2 Social activities. In Aion, there are three types of social activities as follows.

- **Chat:** Users can communicate with other individuals or with the members in the same group such as a party or a guild in which she currently participates. A user can send only a private message to other users for individual communications, while she can broadcast a message to group members for group communications.
- **Friendship:** A user in Aion can make a bidirectional friendship with other user. If user A sends an invitation to user B, and user B accepts the invitation, then the two users become friends. Once a friendship is established, the user can check the status of his/her friend.
- **Group:** Interacting in a group is known as an one of the important activities in MMORPGs [5]. A user in Aion can make or join a group for collaborative activities. There are two major group activities in Aion: a party and a guild. A party is a small group consisting of up to six players. A party tends to be temporarily formed by users with the same goal such as completing a quest or hunting monsters, and be disbanded after achieving the goal. A guild is usually formed for the purposes of social interactions. Hence, members in a guild do not necessarily have the same goal. It was reported that users feel that a guild is an essential element of the social life in online gaming communities [9].

3.2 Aion Dataset

NCSOFT, one of the largest game companies, generously provided us the log-based dataset for Aion, which consists of records for every

user activity described above. The dataset was collected from one of the servers in Aion for 91 days from December 21, 2010 to March 21, 2011. Our dataset includes 94,870 users and their activities. We first summarize the basic statistics of economic activities appeared in Aion in Table 1. As shown in Table 1, the sales at agency and trades are the two dominant economic activities, which are responsible for 85% of the total money shared through the virtual economy. If we only count the deals among users, the market share through the agency and trades increases since the NPC shop is the activity that a user only deals with an NPC. We also summarize the basic statistics of social activities in Table 2.

Activity type	Agency	Trade	NPC Shop	Mail	User shop
# activities	7,107,972	948,123	34,307,016	940,170	57,680
# Users	51,246	48,305	64,266	32,639	8,125
Market share	34.9%	50.4%	8.9%	1.8%	3.9%

Table 1: Basic statistics of economic activities are summarized.

Activity type	Chat	Friendship	Party	Guild
# activities	145,804,652	224,436	5,244,212	40,090
# Users	59,734	29,905	50,192	25,988

Table 2: Basic statistics of social activities is summarized.

4 SOCIAL AND ECONOMIC ACTIVITIES

In this section, we seek to investigate social and economic activities of users in Aion. To this end, we first model the social and economic activities as a multi-layer graph which contains five graphs: (i) agency, (ii) trade, (iii) private message, (iv) party, and (v) friendship. We then analyze the five graphs to understand how users interact with others from social and economic perspectives. Lastly, we examine how users' economic and social activities overlap with one another.

4.1 Graph Model

Figure 1: A multi-layer graph to model the user interactions is illustrated.

We model social and economic activities in Aion as a *multi-layer graph*, which consists of three layers as shown in Figure 1: (i) economic activity layer, (ii) social activity layer, and (iii) friendship layer. A layer represents a group of activities, and may be composed of one or more graph(s), each of which represents a specific type of activity. We model two major economic activities, the agency and the trade as the agency graph (G_{agency}) and the trade graph

(G_{trade}) in the economic activity layer, respectively. Note that we exclude the NPC shop, mail, and user shop activities in our model since (i) the NPC shop does not provide user-to-user interactions and (ii) the mail and user shop activities are responsible for only small portions of the market share. The two graphs in the economic activity layer are directed and weighted, both of which can be commonly represented as three sets, (V, E, W) , where V is the set of users, and E is the set of edges, each of which represents a deal or an exchange through agency or trade, respectively. The weight of an edge is the count of deals (or trades) occurred between two users, and its direction is from the payer (sender) to the payee (receiver). The social activity layer is the union of two undirected and weighted graphs: the private message graph (G_{pm}) and the party graph (G_{party}). An edge of the private message graph indicates the exchanged message between two users and its weight is the message count. An edge of the party graph represents joining to a same party and its weight is the count of the parties joined together (Note that there are multiple parties between two users over time). The friendship layer has only a single undirected and unweighted graph, the friendship graph (G_{friend}). The edge in the friendship graph indicates a friendship between two users.

4.2 Properties of Activity Graphs

We first investigate the graph properties of the five graphs defined above to understand how users interact with others from social and economic perspectives. Table 3 summarizes the properties of the five graphs in terms of number of nodes, number of edges, average weight of edges, number of weakly connected components, clustering coefficient (CC) [29], and average path length (APL) [29]. We find that the portions of nodes that are connected by edges in all the graphs but G_{friend} are mostly around 50%, meaning that half of users interact one another for social or economic purposes. However, we note that not many users have friendship relations with others in Aion. The number of edges in G_{agency} is significantly high, meaning that agency activities are prevalent.

Graph	# nodes	# edges	avg. weight	# components	CC	APL
G_{agency}	51,246	5,255,242	1.35	4	0.1	2.85
G_{trade}	48,305	332,801	3.1	790	0.05	4.98
G_{pm}	52,085	2,845,561	9.65	101	0.1	3.19
G_{party}	50,192	2,513,269	2.09	672	0.07	3.41
G_{friend}	29,905	213,944	-	735	0.04	4.66

Table 3: Properties of the five graphs are summarized.

As described in Table 3, G_{agency} is comprised of only 4 components while there are 790 components in G_{trade} . Moreover, the CC of G_{agency} is higher than that of G_{trade} while the APL of G_{agency} is lower than that of G_{trade} indicating that nodes in G_{agency} are massively connected while G_{trade} is relatively sparse. Similarly, G_{pm} shows higher CC and lower APL than G_{party} , meaning that G_{party} consists of the loosely-connected components. Note that G_{friend} also tends to have a large number of components while its number of nodes is relatively small, implying that friendship activities are likely to be scattered.

We next investigate the distributions of degrees and weights of the two economic-activity-related graphs in Figure 2: G_{agency} and G_{trade} . We first find that both degrees and weights of G_{agency} and G_{trade} follow the power-law distribution with the exponents of

Figure 2: Degree and weight distributions of G_{agency} and G_{trade} are plotted.

2.24 and 1.09. As shown in Figure 2, the node degrees in G_{agency} are higher than those in G_{trade} mostly. Less than 20% and 5% of users deal with only one user through the agency and trade, respectively, while the top 1% users in G_{agency} and G_{trade} have economic relationships with more than 1,552 and 106 users, respectively. On the other hand, the weight distribution shows a reverse tendency; the weights of the edges of G_{agency} are lower than those of G_{trade} . The weights of 82% and 67% of the edges of G_{agency} and G_{trade} are 1, respectively, meaning that most of two users tend to deal only once. Note that the top 1% of edges (in terms of weight) of G_{agency} and G_{trade} have weights more than 6 and 34, respectively. These results reveal that users in Aion tend to deal with more players but less frequently through the agency than trade. This is due to the different usage of the agency and trade; the trade requires that two users need to meet in person while users who would like to use the agency need not rendezvous in the virtual world.

Figure 3: Degree and weight distributions of G_{pm} , G_{party} , and G_{friend} are plotted.

We also examine the distributions of degrees and weights of G_{pm} , G_{party} , and G_{friend} in Figure 3. As shown in Figure 3, the degree distributions of G_{pm} and G_{party} are almost identical, which indicates that users tend to exchange messages and engage in parties with similar number of users. The node degrees of G_{friend} are lower than those of other graphs, meaning that users tend to exchange messages or participate in parties with more users while they are likely to make friendship with relatively less users. This may be due to that users in Aion tend to make friendship carefully. Note that all the degree distributions follow the power-law distribution [2] (with exponents - private message: 1.45, party: 1.53, friend: 1.23). When we look at degree distributions in Figure 3, less than 9%, 2%, 1% of users exchange private messages, form a party, and make a friendship with only one user, respectively, while the top 1% users (in terms of weight) in G_{pm} , G_{party} , and G_{friend} interact with more than 1,051, 905, and 98 users, respectively. Note that the weights of G_{pm} are, in general, higher than those of G_{party} ,

meaning that private messages are more frequently exchanged than party invitations.

4.3 Relations between Economic and Social Activities

We examine how social and economic activities are associated with each other, e.g., whether two users who participate in a party also trade items or money. To this end, we measure whether one activity overlaps with another in two ways: degree overlap and link overlap. We first check the degree overlap by choosing a pair of graphs (e.g., G_{pm} , G_{agency}), and calculate the Pearson's correlation coefficient [31] between the same node's two degrees of the two graphs. Table 4 shows the pair-wise coefficients across the five graphs. Note that we separate in-degree and out-degree for the graphs in the economic layer as they are directed ones. As shown in Table 4, all coefficients are higher than 0.3, meaning that number of interacting users is positively correlated across all the activities. Also, the coefficients between the private messaging (PM) and party, PM and friendship, and party and friendship are significantly high (0.94, 0.75, and 0.72, respectively), which implies that those activities are strongly correlated from a degree overlap perspective, e.g., if a user has many friends, he/she is also likely to chat or form a party with many people. Note that the degrees between trade and other social-activity-related graphs (in the social activity layer) are more correlated than the agency, implying that users who trade with many people tend to be social.

Degree type	Agency-in	Agency-out	Trade-in	Trade-out	PM	Party	Friendship
Agency-in	-	0.49	0.42	0.44	0.48	0.49	0.38
Agency-out	0.49	-	0.47	0.5	0.49	0.49	0.42
Trade-in	0.42	0.47	-	0.76	0.72	0.71	0.64
Trade-out	0.44	0.5	0.76	-	0.72	0.71	0.65
PM	0.48	0.49	0.72	0.72	-	0.95	0.75
Party	0.49	0.49	0.71	0.71	0.95	-	0.73
Friendship	0.38	0.42	0.64	0.65	0.75	0.73	-

Table 4: Degree overlaps between two activities are reported.

We next examine how two nodes connected in one network (e.g., G_{pm}) are also connected in another network (e.g., G_{agency}) to quantify the link overlap. To this end, we compute the conditional probability of a graph (of social activities) when economic activities are given as follows:

$$P(G_{social}|G_{economic}) = \frac{N(E_{social} \cap E_{economic})}{N(E_{economic})} \quad (1)$$

where $N(A)$ is the number of elements in the set A , and E_{social} and $E_{economic}$ are the sets of edges in graphs of social activity layer and economic activity layer, respectively.

Figure 4 shows the conditional probabilities of the three social graphs, G_{pm} , G_{party} , and G_{friend} , respectively, when G_{agency} or G_{trade} are given. The conditional probabilities when G_{trade} is given are higher than those when G_{agency} is given, meaning that social interactions and trade interactions are highly overlapped. In particular, $P(G_{pm}|G_{trade})$ and $P(G_{party}|G_{trade})$ are significantly higher than others (60% and 54%, respectively), which implies that if a pair of players trades items (or money), they are likely to (i) communicate through private messages and (ii) form parties.

To further explore the two cases with high conditional probabilities, $P(G_{party}|G_{trade})$ and $P(G_{pm}|G_{trade})$, we investigate how the weights of edges in the two graphs are correlated. Figure 5

Figure 4: We calculate the conditional overlap probabilities of the three graphs, G_{pm} , G_{party} , and G_{friend} , respectively, when G_{agency} and G_{trade} are given.

plots the weights of the overlapped edges between the trade and social graphs (i.e., G_{pm} and G_{party}). That is, the (x, y) of a dot in Figure 5a indicates the weights of edges in G_{trade} and G_{pm} , respectively. Note that dark dots represent the median of weights of the edges in a social-related graph against the trade graph. As shown in Figure 5b, the weights between the trade and party graphs show a positive correlation; the Pearson's correlation coefficient of weights between the trade and party graphs is 0.44. On the other hand, the correlation coefficient of weights between the trade and PM graphs is only 0.14, which implies a weak correlation. This indicates that if two users form parties, they are likely to trade items (or money) since the members of the same party are likely to trade items to distribute rewards after completing tasks such as fulfilling quests or killing monsters. In other words, party activities may drive trades among party members.

Figure 5: Weights of the overlapping edges between the trade and social graphs (i.e., G_{pm} and G_{party}) are plotted. Each dot indicates a weight of an overlapping edge between G_{trade} and $[G_{pm}$ or $G_{party}]$.

5 UPPER-CLASS ANALYSIS

In this section, we focus on the *upper-class* who plays a crucial role in economic graphs in Aion. To identify the *upper-class*, we first extract the edges for dealing money from the agency and trade graphs, and observe how the income and expenditure through both activities are skewed across users. We identify the top 1% of users in terms of income and expenditure as the *upper-class*, which are characterized in terms of in-game traits, as well as patterns of social and economic activities.

5.1 Skewness of Income and Expenditure

We explore how the income and expenditure through the agency and trade are skewed across the Aion users. To observe the distribution of the incomes and expenditures, we calculate the *Gini coefficient*, a well-known indicator to evaluate the disparity of a distribution in Economics [7]. The Gini coefficient is within the

range of $[0, 1]$, where 0 and 1 represent a perfect uniform and an extremely skewed distributions, respectively.

Figure 6: Lorenz curve and Gini coefficients for income and expenditure are plotted.

Figure 6 shows the Lorenz curve [27] of incomes (or expenditures) where the x-axis is the cumulative share of users from the lowest to the highest income (or expenditure). Obviously, the income and expenditure distributions are highly skewed; a small number of users are responsible for a high portion of the income and expenditure through both the agency and the trade. For example, the top 20% users in terms of income through the agency and trade earn 87.5% and 92.7% of total income, respectively, while the top 20% of users in terms of expenditure through the agency and trade spend 91.0% and 94.6% of total expenditure, respectively. The Gini coefficients for incomes through the agency and trade are 0.83 and 0.89, respectively, and the ones for expenditure are 0.86 and 0.9, respectively, which implies that both income and expenditure are highly skewed to a small number of users. Considering Gini coefficients in real world do not exceed 0.6 for the most countries [6], we can conclude that in-game economy is heavily skewed towards high income users and heavy exponders.

5.2 Characteristics of the Upper-Class Users

We now investigate the upper-class from an economic perspective, the top 1% users (948) in terms of income or expenditure through the agency or trade. They can belong to at least one of the following four groups: *Agency_{inc}*, *Agency_{exp}*, *Trade_{inc}*, and *Trade_{exp}*. For example, *Trade_{inc}* is the set of the top 1% users in terms of income through the trade. The total number of the users across the four groups is 2,371, among which 1,211 (51%) users belong to at least two groups.

Figure 7: Levels of users in the upper-class on the last day of our measurement period are plotted.

5.2.1 In-game Traits and Social Activities. We first observe the level of each user on the last day of our measurement period. Note that a level of a character reflects both the degree of achievements and the potential economic ability in a virtual world. That is, if a

user finishes an in-game task like hunting monsters or completing a quest, the user obtains experience points, and the level of the user can increase if the accumulated experience points of the user reach at some criteria defined by game designers. A user becomes eligible to carry out more difficult in-game tasks that give more rewards (money, items, or points) as his/her level gets higher. Note that the maximum level of a user is 55 in Aion at the moment of our measurement.

Figures 7a and 7b show the histograms of the levels of the top 1% (the upper-class, plotted at top) and non-upper-class (plotted at bottom) users in terms of income and expenditure through the agency (left-side) and trade (right-side). The number of users whose levels are maximum (55) is significantly high in all cases, indicating that the upper-class users, in general, tend to achieve the maximum level. Interestingly, a substantial portion of users in the upper-class have levels of 10 or less except the *Agency_{exp}*. We suspect that these users may not be normal users from the following reasons. A user in Aion starts a game with a character equipped with cheap items and a small amount of money. In general, there can be two ways that users earn money through economic activities: (i) paying efforts on earning items or money through in-game tasks, e.g., hunting monsters or completing quests, and (ii) receiving money from other users. Since it is not possible to stay at low levels if users earn much money from in-game tasks (i.e., they should be at high levels as they obtain experience points), we conjecture that the users who are at low levels (10 or less) but belong to the upper-class can only earn money from other users without in-game tasks, which may not be the normal economic activities in Aion. Note that the portions of low level (10 or less) users are higher in *Trade_{inc}* and *Trade_{exp}* than those in *Agency_{inc}* and *Agency_{exp}*, implying that such abnormal behaviors tend to appear in the trade activities than the agency activities.

Figure 8: Distributions of playtimes of users in the upper-class are plotted. The average playtime is displayed as a small horizontal line in the middle.

We next examine the playtime of each user in the upper-class in Figures 8a and 8b. Obviously, the upper-class users are likely to spend more time for playing Aion, than normal users. Overall, the upper-class users play 7.7 hours a day on average while other users (i.e., non-upper-class) play only 48 minutes a day on average. Interestingly, the users in *Agency_{inc}* and *Trade_{exp}* show hourglass-like distributions while the playtime of users in *Agency_{exp}* follows a normal distribution. The playtime at the waist of the hourglass in case of *Agency_{inc}* is around 15 hours, meaning that there are heavy users who spend more than 15 hours a day (on average) for 3 months. On the other hand, the playtime of users in *Trade_{inc}* is skewed downwards and their median playtime is less than half of

other upper-class users, i.e., 3 hours, indicating that the upper-class users in terms of income through the trade are likely to play the game for relatively short times.

Figure 9: The distributions of the numbers of private messages a user sends and parties a user joins are plotted.

We further examine the patterns of social activities for the upper-class and non-upper-class users by counting the private messages a user sends and the parties a user joins. Figures 9a and 9b show the distributions of the numbers of private messages sent and parties over the four upper-class and non-upper-class users. As shown in Figure 9a, the users in *Agency_exp* send more private messages than others while the users in *Trade_exp* are unlikely to send messages. Around 70% of the users in *Agency_exp* send more than 1 K messages while only 12% of non-upper-class users and 12% of *Trade_exp* users send more than 1 K messages. This indicates that the upper-class users who spend a large amount of money through the agency (i.e., heavy buyers) are likely to be talkative, but the upper-class users who send much money through the trade do not tend to talk with others. Interestingly, the upper-class users in *Agency_inc* and *Trade_inc* show similar patterns in terms of the number of private messages. 35% and 32% of the users in *Agency_inc* and *Trade_inc*, respectively, never send any private message. However, there exist some users in *Agency_inc* and *Trade_inc* who would like to frequently talk with other users. Note that the distributions of the numbers of private messages and parties show a similar tendency.

5.2.2 Degree of Economic Activities. We next investigate whether the upper-class users pay more attention to economic activities than social activities, or vice versa. To this end, we quantify the degree of economic activities by computing the ratio of the number of economic activities to the number of social and economic activities as follows.

$$R_{eco} = \frac{(\# \text{ of economic activities})}{(\# \text{ of economic activities} + \# \text{ of social activities})} \quad (2)$$

The ratio is one if a user only plays economic activities and is zero when a user plays only social activities.

Figures 10 and 11 show the distributions of R_{eco} values for the four upper-class types. The x-axis represents the average play time (hours) that a user spends for a day, and y-axis indicates R_{eco} of the user. For visualization purposes, we divide the users (dots) into four regions by drawing two lines, $x = 15$ and $y = 0.9$, and compute the portion of users in each region. We separately plot the users whose levels are 55 and less than 55 into Figures 10 and 11, respectively.

As shown in Figure 10, high portions of users in *Agency_inc* and *Trade_inc* are mostly located either in the bottom-left or upper-right regions, and the portions of the users in the bottom-left region are

higher than the ones in the upper-right region, indicating that users who have much income are either (i) ones who play games for moderate times and interact with others to some extent, or (ii) heavy game players who mostly concentrate on economic activities. Note that the portion of the users in *Trade_inc*, whose play times are less than 15 hours a day and R_{eco} values are less than 0.9, is higher than that of the ones in *Agency_inc* in the same region, implying that users who gain a large amount of money through the trade tend to be more sociable while heavy sellers through the agency are more likely to spend most of their time on playing the game.

Figure 10b shows that almost (99.5%) of the max-level users in *Agency_exp* are in the bottom-left region where their average play times are less than 15 hours a day and R_{eco} values of them are less than 0.9, meaning that users who spend a large amount of money through the agency are likely to invest relatively less time for playing the game and likely to socialize with other users. On the other hand, 63.0% of users in *Trade_exp* play games more than 15 hours a day and their R_{eco} values are higher than 0.9, which implies that users who send a large amount of money tend to spend most of their time on playing, but not on socializing with others.

Figure 11 next shows the distribution of the R_{eco} values of the upper-class users whose levels are less than 55. Overall, the scatterplot is substantially skewed to the left side; 94.2%, 97.4%, 98.7%, and 95.2% of these users are in the left region, which indicates that the upper-class users whose levels are less than 55 tend to play games for relatively short times. Interestingly, significant portions of the users in *Agency_inc*, *Trade_inc*, and *Trade_exp* have high R_{eco} values. For example, R_{eco} values of 88.5%, 71.5%, and 88.4% of the users (whose levels are less than 55) in *Agency_inc*, *Trade_inc*, and *Trade_exp* are higher than 0.9, respectively. This implies that these users tend to concentrate more on economic activities rather than social activities. Note that the portion of the users whose levels are less than 55 in *Agency_exp* and whose R_{eco} are higher than 0.9, is relatively small (58.2%), meaning that these users, who heavily spend money through the agency, tend to be relatively social.

In summary, the upper-class users exhibit distinct in-game traits and socio-economic activities. A significant portion of the upper-class users reach the max-level in Aion (i.e., 55) while there are some low level upper-class users who are suspicious as they seem to gain much money from other users without in-game tasks, which may not be the normal economic process in Aion. Our analysis further reveals that these low level upper-class users are unlikely to socialize with others. By analyzing the max-level upper-class users, we show that the four upper-class types show different behaviors in terms of in-game traits and socio-economic activities. The max-level upper-class users in *Agency_exp* tend to socialize and to spend less than 15 hours a day in playing the game while a high portion of the users in *Trade_exp* are likely to play the game more than 15 hours a day, which seems to be not humans, and hardly socialize. These patterns also appear in *Agency_inc* and *Trade_inc*.

6 UPPER-CLASS USERS ASSOCIATED WITH REAL MONEY TRADE

We now focus on the suspicious upper-class users who show distinct or even abnormal patterns in the previous section. In particular, we investigate how the upper-class users who are at low level,

Figure 10: Playtimes and R_{eco} of the upper-class users whose levels are 55 are plotted.

Figure 11: Playtimes and R_{eco} of the upper class users whose levels are less than 55 are plotted.

play the game much more than others, or rarely interact with other users, are associated with the Real Money Trade (RMT). This may be an illegal behavior that gathers in-game money in exchange for real-world money [22]. To this end, we first introduce the general RMT process appearing in MMORPGs. We then investigate how the suspicious upper-class users are associated with the entities in the RMT in Aion.

6.1 Introduction to Real Money Trade and Gold Farming

Figure 12: The RMT process in the virtual world is illustrated.

The goal of the RMT is to gather some game money in exchange for real-world money. Previous studies have discussed its adverse effects on the virtual economy [10]. Figure 12 illustrates the overall process of RMT. The RMT consists of three participants as follows:

- **Gold Farmers** are the users who focus on collecting virtual money by repeatedly conducting in-game activities such as hunting monsters. To maximize the efficiency of such activities with minimal human labors, they often use illegal automatic programs (i.e., bots) that not only control a user's in-game actions like moving in a virtual world, but also conduct complex behaviors such as hunting monsters

and gathering booties. Many researchers have pointed out that the bots are likely to spend much time in playing game abnormally [16]. Gold farmers then exchange their items into virtual game money. They often sell items through virtual markets such as the agency in Aion, or sometimes sell items to other RMT participants, e.g., through the trade in Aion, to avoid possible detections and sanctions imposed by game providers. Gold farmers finally send the obtained game money to money launderer(s).

- **Money Launderers** receive game money from gold farmers (through the trade) and exchange the received virtual game money into real-world money. A well-known way to exchange in-game money into real world money is that, money launderers send in-game money to consumers through the trade system and receive real-world money back. Since the deals of real-world money are not recorded, researchers have tried to predict RMT deals based on trade records, e.g., a user sends substantial money to another without receiving back any corresponding virtual goods.
- **Consumers** are the users who 'buy' in-game money with real-world money. It has been reported that they are eager to achieve a high level in a short time with minimal human labors [1, 22, 24].

It has been reported that gold farmers who use bot software tend to play extremely much time, spend time more on harvesting items from hunting, and hardly socialize [3]. Gold farmers in Aion can (i) earn in-game money by selling the items in the agency, and (ii) send the obtained in-game money to a few designated launderers through the trade. Therefore, in our study, the upper-class users who meet the following four criteria can be regarded as gold farmers: (i) they belong to *Agency_inc* or *Trade_exp*, (ii) their levels are 55, (iii) the average playtime per day is greater than 15 hours, and (iv) the R_{eco} value is higher than 0.9 which indicates those users rarely engage in social interactions with others.

On the other hand, money launderers are unlikely to be online to avoid possible inspection from the game provider [21]. That is,

they try to minimize the number of online activities. The levels of money launderers tend to be low since achieving a high level takes resources, which may be useless for money trading. When they trade money, they are likely to send all the money they have, while normal users send a small portion of money they have. As their concerns are mostly trading money, money launderers hardly participate in social activities such as sending private messages or joining a party. In our study, we deem the upper-class users who meet the following three criteria as money launderers: (i) they belong to $Trade_{inc}$ or $Trade_{exp}$, (ii) their levels are 10 or less, and (iii) their R_{eco} values are higher than 0.9.

In our dataset, we finally identify 470 (19.8%) gold farmers and 382 (16.1%) money launderers among all the upper-class users. Note that our criteria may not be rigorous; there can be other gold farmers or money launderers who do not meet our criteria, e.g., launderers whose levels are 55. We conservatively select the gold farmers and money launderers based on our criteria from the upper-class users, who play crucial roles in the socio-economic system of Aion.

6.2 RMT and Virtual Economy

We now investigate how gold farmers and money launderers identified in the above affect the virtual economy of Aion. To this end, we first observe the ratios of gold farmers and money launderers in the four upper-class groups in Figure 13. Overall, the portions of users involved in the RMT are different across the different upper-class groups. As shown in Figure 13, 32.8%, 40.6%, and 69.4% of users in $Agency_{inc}$, $Trade_{inc}$, and $Trade_{exp}$ participate in the RMT system, respectively. However, there is only one gold farmer (0.15%) and no money launderer in $Agency_{exp}$, which is natural because participants in the RMT are unlikely to buy expensive high-quality items. Thus users who spend much money through the agency are not either gold farmers or money launderers.

Figure 13: Ratios of gold farmers and money launderers in four upper-class groups are plotted.

Interestingly, there are some gold farmers in $Trade_{inc}$, who may gather money not only through farming activities but through the trade. Similarly, some money launderers are observed in $Agency_{inc}$, who may earn money by selling items. These money launderers may receive items from gold farmers and exchanges them into money through the agency deals. Note that a substantial portion (about 70%) of users in $Trade_{exp}$ are either gold farmers or money launderers, implying the most of the upper-class users in $Trade_{exp}$ participate in economic activities as a part of the RMT.

We finally investigate how much money in the RMT is responsible for all the money dealt through the trade system in Aion.

Figure 14 shows the market share (i.e., amount of money) of each trade among gold farmers, money launderers, and the other normal users. Interestingly, more than half of total money exchanged through the trade are related to RMT participants, and only 41.8% of money across all the trades are dealt among normal users. In particular, the portion of money from money launderers to normal users is around 34%, which seems to be the case of exchanging in-game money into real-world money. Note that the gold farmers and money launderers are selected only from the upper-class, but they are responsible for a substantial market share of ‘all’ trades in Aion. If we look at the agency activities, we observe that identified gold farmers and money launderers earn 9.3% and 2.7% of total sales in the agency, respectively, meaning that more than 10% of money over the agency deals is involved in the RMT.

Figure 14: Market shares of each trade among gold farmers, money launderers, and the other normal users are plotted.

7 CONCLUSION

This paper comprehensively studied socio-economic activities of users in Aion. In particular, we investigated (i) how users participate in economic & social activities, (ii) how upper-class users show distinctive behavior in terms of in-game traits and social/economic activities, (iii) how upper-class users are associated with the RMT. By modeling and analyzing the socio-economic activities as a multi-layer graph, we showed that the social interactions are highly correlated with the trade activities. We also found that virtual economy in Aion is heavily inclined to a small number of upper-class users, and a significant portion of them reach at the max-level and tend to either (i) have many social interactions with others or (ii) play extremely much time with no social activity. Our in-depth analysis on the upper-class users revealed that some suspicious upper-class users, who are at low-levels, play the game extremely much more than others, or rarely interact with other users, are associated with the RMT. We further revealed that more than half of total money exchanged through the trade are associated with the upper-class users who involve in the RMT. We believe our analysis can provide an important implication on how people participate in the virtual economy and how people interact to each other.

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