Crime Scene Reconstruction: Online Gold Farming Network Analysis

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***Abstract*— Many online games have their own ecosystems, where players can purchase in-game assets using game money. Players can obtain game money through active participation or "real money trading" through official channels: converting real money into game money. The unofficial market for real money trading gave rise to gold farming groups (GFGs), a phenomenon with serious impact in the cyber and real worlds. GFGs in massively multiplayer online role-playing games (MMORPGs) are some of the most interesting underground cyber economies because of the massive nature of the game. To detect GFGs, there have been various studies using behavioral traits. However, they can only detect gold farmers, not entire GFGs with internal hierarchies. Even worse, GFGs continuously develop techniques to hide, such as forming front organizations, concealing cyber-money, and changing trade patterns when online game service providers ban GFGs. In this paper, we analyze the characteristics of the ecosystem of a large-scale MMORPG, and devise a method for detecting GFGs. We build a graph that characterizes virtual economy transactions, and trace abnormal trades and activities. We derive features from the trading graph and physical networks used by GFGs to identify them in their entirety. Using their structure, we provide recommendations to defend effectively against GFGs while not affecting the existing virtual ecosystem.**

***Index Terms*— Online games, game bot, gold farming group, MMORPG.**

I. Introduction

IN RECENT years, online games have attracted much attention, and have become a fascination for many people in a wide age range. Massively multiplayer online role-playing games (MMORPGs) are one of the most popular forms of online gaming, with millions of dedicated users and fans worldwide. MMORPGs are designed in a way that requires cooperation between players to accomplish difficult tasks, and eventually to boost the number of players who interact with one another in the virtual game world. The number of active users and volume of their interactions measure the success of an MMORPG. To that end, one of the important aspects of MMORPGs is their virtual economy. Virtual goods and in-game currency are critical to increasing the survivability of in-game characters by improving their power and reputation. Virtual goods are designed to be acquired through substantial time investments ranging from several months to even years of active participation, and determine the level of a character in the virtual world. Eager to achieve a high level in a short time, some users employ real money to gain experience or to obtain valuable virtual goods, an aspect allowed by design in MMORPGs for profitability.

In the game world, players can trade items. Game items and virtual money trades are restricted to the game world. However, as games become more popular, cyber assets become tradable outside the game world and become valuable assets in the real-world economy too. As a result, the ecosystem of gold farmers has arisen. Professional gold farmers are players likely from poorer regions who play games an entire day and sell their obtained virtual goods in order to earn the same wage as much as (or even more than) what they might earn for real work.

Gold farming groups (GFGs) are organizations that gather and distribute virtual goods for capital gain in the online game world [1]–[3]. GFGs hire low cost laborers to establish their business by starting from a small business and growing into a large enterprise. This behavior has recently drawn considerable attention from economists and sociologists as a nexus where millions of rich and poor, real and virtual, and developed and developing worlds intersect [4].

To provide a boost and vitality to the online game world, one of the important aspects is to manage the virtual economy well. Therefore, online game designers and operators (companies) thoroughly consider and maintain economic factors in the game system. For example, online game companies are continuously monitoring the possible inflation rate and the status of redistribution of cyber-wealth, configuring the drop ratio of items (e.g., armors and weapons), the total amount of currency in circulation, and the price of staple (raw) commodities.

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In-game trading often leads gamers with limited time to purchase virtual capital with real money for powerful armors, weapons, and skills—collectively called assets. Such assets make them capable of exploring larger parts of the game world and confronting more exciting and challenging enemies. Eventually, such progress in levels increases their social standings, a goal in and of itself for many games [2], [5]. In the middle of this process, GFGs usually employ bot programs—an artificial intelligence (AI) program that can play a game without human control to increase the efficiency of gathering money. Furthermore, GFGs spread malicious programs (malware) to steal money from the accounts of other users in the game. To that end, gold farmers can be categorized into two types. The first type is micro-workers. GFGs hire some low cost micro-workers who play games to earn money through labor-intensive work [6]. The second type is unmanned and automated gold farmers, thus, GFGs that use bots.

To detect GFG activities and control their underground economy, online gaming companies make a full range of efforts. They actively hire monitoring personnel and deploying log analysis systems to distinguish game bot users from normal users. Thus far, the existing methods for detecting GFGs tend to distinguish between bots and normal players using data mining techniques and Turing test-based techniques. These techniques distinguish bots from human players using behavioral patterns or their response to interactive tests. The race between online game companies and bot developers has resulted in considerably more elusive and human-like bots [6], thus avoiding the newest and most advanced detection techniques.

The end goal of our investigation is to identify an entire GFG, not only individual bots that compromise part of the trading networks within GFGs—as done in the literature. As a first step towards this goal, we extract the trading network of GFGs from a larger and richer trading network. Then we separate each GFG using community detection methods to identify them in groups. In a second step, we classify the characters in a GFG based on their roles by considering a selective banning scenario to regulate and enforce correct economic norms.

As with most MMORPGs that require a monthly or annual fee to access the game, even bots and their existence can be viewed profitable from an economic perspective. Furthermore, bots can be regarded as "good" customers using the traditional customer relationship, because bots are incentivized to login every day and actively participate in the game play (although their real purpose is to earn virtual money). To this end, banning all bot (or misbehaving) players may not be the best method for thwarting misuse. Accordingly, rather than focusing on a binary classification of "good" and "bad", we extend the view into a multi-class problem by identifying malicious users within a GFG into three types: gold farmers, merchants, and bankers. This method is helpful for blocking malicious users selectively as opposed to massive banning operations, which may harm the entire game. As a result, using such selective banning operation we can precisely target and weaken GFGs while minimizing the harm to the existing ecosystem.

A. Contributions

An in-depth characterization of the underground economy of MMORPGs highlighting interactions between players within GFGs is introduced as a major contribution in this paper. We perform this characterization using real-world traces of a popular MMORPG called AION. Then, we establish guidelines and rules for distinguishing between various player types in the GFG ecosystem: gold farmers, merchants, and bankers. For that, we utilize a deep context understanding of the analyzed game, the rules of various characters, and the operation of GFGs. Third, using insight from measurements and characterizations, we devise a rule-based community detection mechanism that effectively detects GFGs from the rest of characters in the game. Our mechanism classifies GFG characters based on their role into gold farmers, merchants, and bankers.

Many interesting findings and insights highlight the novel measurement aspects in our study. We followed the GFG network dynamics by banning operation for 12 weeks and found that banning efforts employed by companies do not stop GFG from recruiting new gold farmers. On the other hand, our recommendations, which differentiate between malicious characters and suggest banning bankers, characters central to GFG operation, has shown to be more effective in damaging GFGs operations with small and selective banning efforts.

II. RELATED WORKS

Gold farmer detection methods have evolved over the years, and the literature on the problem can be classified into three generations of related works. The first generation of such methods is signature-based, and utilizes client-side bot detection such as antivirus programs or CAPTCHA-based techniques [7], [8]. However, the first generation of commercial products could be thwarted using techniques learned from reverse engineering. Also, methods using CAPTCHA are known to be user-unfriendly, and contribute to user annoyance. Finally, solving CAPTCHA has generated a thriving business that uses mechanical Turks utilized by underground players.

The second generation of methods focused on data-mining techniques, and used server-side bot detection systems [6], [9]–[12], which focused mainly on distinguishing between a bot and a benign player by analyzing server-side log files. Such techniques are widely used commercially and are coupled with logging techniques and various data mining algorithms for highly accurate bot detection. However, making a variant of an existing bot that can generate new behavioral patterns to thwart an existing detection technique is very easy and heavily utilized by gold farmers. Moreover, this method targets gold farmers individually. Companies have less insight of who belongs to the same group, and GFGs fight banning by continuously creating new gold farmers, making current banning efforts ineffective.

The third generation methods are a surgical strike policy [13], [14]. They can detect all industrialized GFGs by group assuming that members in a group have frequent interaction and abnormal patterns. Because GFGs have the goal of economic achievement, the trade network provides

TABLE I
GOLD FARMERS' DETECTION METHODS AND GENERATIONS

Gen.	Description	Method
1st	Signature-based, client side bot detection	Process monitoring CAPTCHA [7, 8]
2nd	Data mining-based, server-side bot detection system.	Behavior analysis [1, 9, 10], party play analysis [6], chatting pattern analysis [14], and self-similarity based analysis [16].
3rd	Surgical strike-based, GFG detection system.	Trade network analysis [5, 13, 14], social network analysis [15], contagion analysis [17].

hints to identify GFGs. In [13] and [15], we detected GFGs based on the analysis of trade patterns merely based on the free money ratio; however, we could not detect GFGs group by group. We classify the role of each character (gold farmers, merchants, and bankers) in the GFGs. Gold farmers only collect game goods and when a certain amount of game goods are collected they give the game money to the banker and items to the merchant. The banker collects all game money from GFG characters, and sells the game money for real money. The merchant collects items from the gold farmers and sells them for game money. The merchant gives money earned from the items to the banking characters.

The literature on the detection methods on gold farmers and the corresponding generations is listed in Table I. As GFG detection methods are developed, so are their countermeasures. GFGs always prepare their spare gold farming characters and distribute their game money in various accounts to mitigate banning. Previous measurements for differentiating between GFG and normal user groups are based on statistical methods, data mining, and network feature extraction. These measurements focus mainly on distinguishing between GFGs and normal players by analyzing server-side logs. These measurements can easily detect actively playing GFG characters such as bot players with abnormal or extreme playing patterns. However, GFGs are always ready to reintegrate and change their playing patterns if they are detected and banned by game companies. For effective GFG detection, one needs to observe GFG changes several times for a certain period. This observation can unveil potential gold farming characters and address GFG reintegration before they work normally again. Such long periods of observation improve detection and predict how GFGs affect the economy.

III. PRELIMINARIES

In the following, we review the preliminaries. First, we outline the terminology used in this paper. Then, we outline concepts related to the GFG ecosystem. Finally, we provide a summary of the method used in this work for detecting GFGs.

A. Terminology

1) Character: In MMORPGs, a user operates several characters, where the character is an avatar. Each character owns her unique features of appearance, level, virtual goods, etc.

2) BOT: A game bot is a well-crafted AI program designed for doing tedious and labor-intensive jobs on behalf of human players. It automatically recognizes targets, hunts them, and gains virtual money or items without human player's direct control or intervention. Leveraging the game bot, gold-farmers can gain virtual money and goods efficiently.

3) Gold Farming Group: The main goal of the gold farming group (GFG) is to gain cyber money from online games. In general, a gold farming group operates numerous machines in a physical location and runs multiple client programs on each machine simultaneously. A GFG minimizes the resource usage and costs, thereby making profits. Regardless of whether game bots or laborers play the game, this abnormal activity affects the game ecosystem in a negative way.

4) Economic Activities: A user can exchange or give items using the trade interaction. A user can also open a shop, sell game items, and use an agent to sell or buy items, all of which are common economic activities.

5) Trade Network: The trade network represents interactions between users in the virtual world. When a userA gives userB items or money, or exchange virtual goods, they both are represented in the trade network as nodes and an edge is established between them.

6) Free Money and Items: A user gives such (virtual) money and items away in an economic activity without any payback. We call this activity free money/item trade. The free money/item network refers the trade network that reflects the free money/item trade.

7) Free Money Ratio: Defined as the ratio between the number of free transactions (money, item, or both) and the total number of transactions. The free money ratio measures the level of abnormality of a user's economic activities.

8) Agent: An agent is used to mediate the trade between individual users. Through an agent, users cannot have free money/item trade. Whether the user has the trade through an agent or not is a feature to differentiate GFG members and normal users.

9) Economic Scale: A scale used to express how much a GFG makes in-game money and items. Items are converted to the game money with the average value and prices applied when they are sold.

B. The GFG Ecosystem

When any two characters exchange items or game money, an in-game trade log is generated. In general, players exchange items for other items or money of an equivalent value. However, in some cases, this exchange occurs even when the values of two items are quite different [13], [15]. For example, a user gives an item to other users as a present. However, GFG members give items or money to the character in a higher position to accumulate game items and money in the GFG. Accordingly, the inequivalent trades between GFG members are frequently observed. The free money and items are then sold to buyers who are normal users. To facilitate such process, the GFGs consist of three types of characters: gold farmers, merchants, and banking characters, as shown in Fig. 1, according to the roles as described in Table II.

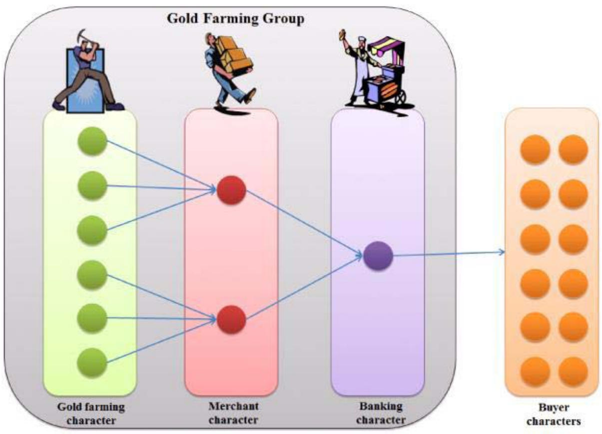


Fig. 1. Illustration of GFG structure.

TABLE II

ROLE SEPARATION RULES FOR GOLD FARMERS (GF), MERCHANTS, BANKERS, AND BUYERS

		Characteristics
Gold farmers	-	Characters who transfer free money to other characters repeatedly and in a unidirectional manner
	-	Characters who have not received anything ever
Merchants	-	Characters who receive free money repeatedly
	-	Characters who transfer free money to other characters repeatedly
	-	Not novice characters (according to game rules, a novice character cannot sell items)
Bankers	-	Characters who receive free money repeatedly
	-	Characters who transfer free money to other characters repeatedly
	-	Novice characters
Buyers	-	Characters who receive free money from a banking character one or more items

Gold farmers repeatedly hunt (game) monsters and harvest craft materials to earn game money and items. Collected items and game money are delivered to merchant characters, and the merchant characters sell the items for game money. The game money from gold farmers and the money acquired through item trade by a merchant character flow to banking characters. Merchant characters receive the free money repeatedly and transfer the free money to other characters repeatedly.

The banking characters possess most of the game money in the GFG, and focus mainly on selling the game money for real money. The banking characters do not play the game, but focus on trading game money because they manage a large amount of it. Hence, they have to keep their account safe from accusations by other users and blocking by the game company. When they are blocked, the game assets in the GFG are seized and written off from the market, causing significant damage to the GFG. Users who want to have high-level characters easily purchase game money for real money from these banking characters. Because of these illegal trades, the economic balance of the game collapses because, for example, an abnormal increase in the amount of game money and items causes inflation. In addition, gamers who buy goods with real money quickly achieve a high level. Those users who do not follow typical steps cause rapid consumption of the game content, which shortens the game lifecycle.

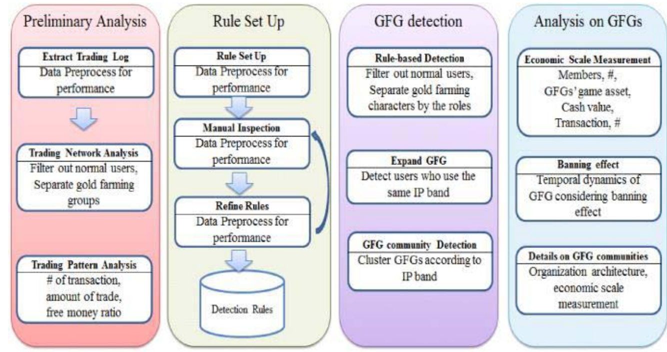


Fig. 2. Framework for tracking GFGs.

Fig. 2 shows the proposed framework in details by highlighting four phases, namely preliminary analysis, rule set up and construction, GFG detection, and in-depth GFG analysis. The detection framework includes two major components: rule-based detection and GFG expansion using (physical) network features of the (potential) GFG. In the following, we provide the details of both phases.

C. Rule-Based Detection

First, we develop a set of strict rules that can be applied for GFG detection. We set such seed rules with 100% accuracy and verify that accuracy through manual vetting and inspection. To develop such detection rules, we perform a thorough inspection of trading patterns and the trade network. We manually select initial characters with abnormal trading patterns and behaviors as seeds for a high-fidelity ground truth, and use them to explore and construct the GFG. To construct the GFG, we run an expansion process to cover a large GFG based on the trading relationships among characters with the initial seeds found in the GFG. The characters with frequent trades with the initial seeds are also considered suspicious. However, suspicion is sufficient to determine the fate of a character: we add suspicious characters to an expanded GFG through an additional step of vetting and manual inspection. We call the outcomes of this process the initial expanded GFG.

D. GFG Expansion Using Network Features

After setting up the initial GFG and a slightly expanded one using rules, we need an efficient expansion method to automate the community discovery process and reduce the amount of manual inspection. In order to achieve this goal, we devise a method that utilizes (physical) network connection information. In general, GFGs operate numerous machines in a physical location, where each machine runs multiple client programs simultaneously. The members in a GFG naturally have similar (physical) network information that can be used to attribute their network and geographical location. Using this information, we refine the expanded network and dissect the resulting network through in-depth analyses to understand character features and their role in the game ecosystem, and how they are affected by actions taken by the game company.

IV. GFG DETECTION

A. Dataset

We use the anonymized trade logs from the MMORPG called AION, published by NCSoft, a leading game company. AION is a popular MMORPG with approximately 3.4 million subscribers [14]. Our dataset covers the logs of three months starting from April 9, 2010 is collected from a server among 17 servers. We use the data to gain insight into GFGs and their activities, and to develop mechanisms for identifying characters that belong to such groups. Each trade log has a unique logID based on the trade type; item or money, and the forms of trade; personal, shop, or agent trade. When character A gives an item (or money) to character B, A has a sending log and B has a receiving log, and both include the item identity and the number of items in the transaction. Additionally, the total number of items a character possesses is recorded. When character A and B have a corresponding log, then the transaction is considered successful. The size of the daily trade log is 17 million on average. We used the first month data to detect GFGs and used the second and third months of logs for analysis of the detected GFGs. During the first month of activities, 39,854 characters had trades. We had records of 3,248,986 transactions. Among them, we excluded the logs related to trades formed by shop and agent not usually performed by GFGs. As illustrated by the framework in Fig. 2, two phases of GFG tracking are general trading analysis rules, and strict rule setup.

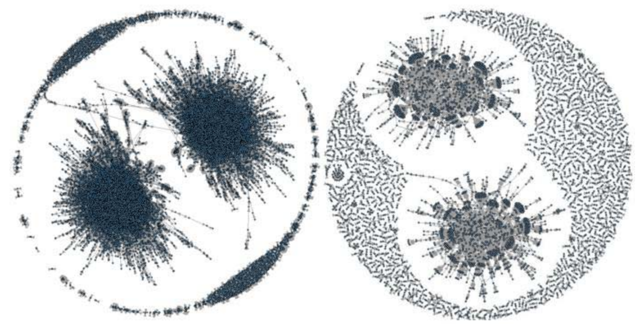
Using the framework in Fig. 2, we describe measurements of the trade network analysis and detection rules setup for GFGs. As indicated above, using the framework in Fig. 2, two phases of GFG tracking are general trading analysis rules, and strict rule setup. In the following subsections, we highlight both phases through a set of measurements.

B. Ground Truth

Obtaining ground truth is a major challenge to many previous works. Fortunately, we have a ground truth that is obtained using manual inspection by game monitoring professionals (humans), thus avoid this issue altogether.

The game company hires game masters (GMs) who monitor the game world and detect malicious users. They have the ability to observe other characters without being noticed. To reduce false positive errors in banning, GMs determine banning targets by observing users in the game world and coding them. When the three more GMs agree on banning a user, the user takes a banning decision. This reduces false positive errors due to the GMs' subjective bias or mistakes. With long period of observation by professionals, we build a ground truth dataset of gold farmers.

However, manual inspection is not a silver bullet to build ground truth data. First, manual inspection is labor intensive thus it is an expensive approach. Second, ground truth data also needs to be updated continuously to respond to new and evolving bots with updated behavioral patterns for evasion. In a recent work [16], the authors also collaborated with the same game company to build ground-truth data with a long period of manual inspection, and they introduced an automatic maintenance method to reduce the continuous manual inspection efforts, which also can be used to improve the process of obtaining ground truth in our work. Upon establishing their behaviors, gold farmer accounts are banned. Once banned, those accounts cannot be used to log in the game, and assets associated with the account are confiscated. If the banned users do not appeal the banning, we conclude it is a bot and use that towards our ground truth. AION operator provides a petition system to save innocent users from the risk of being misclassified.



(a) (b)

Fig. 3. Trading networks: (a) entire trading network (b) free money/item network.

Most of banned users accept the decision of the company, although some file complaints. In response, the company should provide detailed evidence why users are banned. Thus, the company takes a considerate and defensive action towards bot users. This defensive action and the manual inspection may generate false negatives. To resolve the false negative issue, the company generalizes the behavior patterns of banned users, derive rules from the generalization and apply the derived rule to detect unobserved malicious users. The movement, communication and play patterns are widely adopted to reduce false negative errors [18]. In this work, we used the trade pattern and physical network information as a new feature for the same purpose.

C. Trading Network Analysis

We construct the entire network shown in Fig. 3(a), and the free money and items network shown in Fig. 3(b) based on the graph formulation in Appendix. AION has two tribes that cannot interact with each other, thus they form two giant components. From this formulation, we make several observations. First, we easily observe that the free money and items network has many isolated sub-networks, whereas the entire network is somewhat enmeshed. To that end, we consider those abnormal groups for further investigation to trace the trails of black money. Both networks in Figs. 3(a) and 3(b) have two giant components. The nodes in the outer circle area are characters who have no trade with the central nodes.

By comparing the two graphs, we found differences between them. In Fig. 3(b), a character distributes the game money for free to numerous other characters, which results in a fan-shaped distribution in the trade network, as shown in Fig. 4. This fan-shaped distribution is the signature for an anomalous

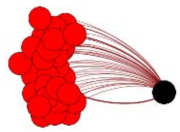
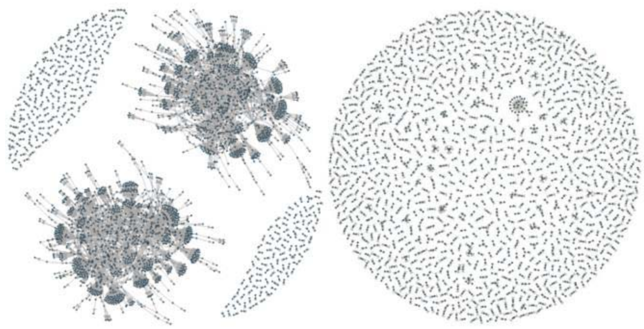


Fig. 4. Game money distribution.



(a) (b)

Fig. 5. Free money network and free item network: (a) free money network, (b) free item network.

pattern in the trade network. Normal users tend to give items and money to their limited friends as a gift. In other cases, players exchange items and money with other characters, and do not give them free. However, gold farmers send acquired items to a banker or a merchant frequently, and thus their trade network has a fan shape.

D. Free Money/Items Network Decomposition

We decompose the free money and item network in Fig. 3(b) into two networks: free money and free items. We plot the outcomes of the decomposed networks in Figs. 5(a) and 5(b). In the first graph, we observe that there are various network structures of the game money distribution that differ from those in Fig. 4, alluding to the possibility of detecting GFGs only by considering the free money and item networks extracted from the entire trading network. However, there are many benign characters in the free money and item network who would be victims by association. Therefore, the detection mechanism and network need to be refined considering other features.

E. "Follow the Money"

As shown in Fig. 5(a), each chunk of the connected nodes in the free money network shows the pattern of Fig. 4. However, in Fig. 5(b), the free item network has a few abnormal distributions similar to Fig. 4. Therefore, we hypothesize that the gold farming network can be tracked using the free money network, but not the free item network. Furthermore, after removing the item trade network, we realize that normal users are also excluded as a side effect of removing free item trade components.

As Fig. 1 shows, the gold farming network has more than three tiers. Thus, we remove networks with less than three tiers, as shown in Fig. 6.

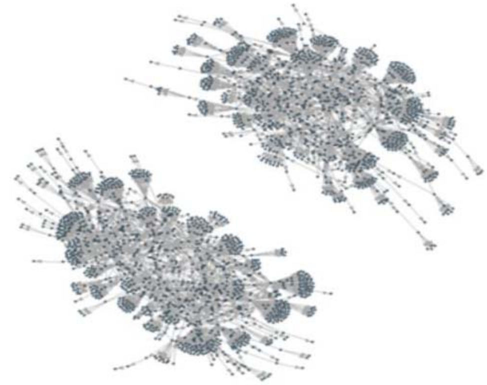


Fig. 6. Free money networks with more than three tiers.

TABLE III

NETWORK INFORMATION: MONEY IS ESTIMATED IN US\$. COLUMNS FOR FIGS. 3(A) TO 5(B) ARE STATISTICS FOR SUCH NETWORKS IN THE CORRESPONDING FIGURES. DEGREE, TRADE, AND (PATH) LENGTH ARE AVERAGE PER USER. NUMBER OF PATHS IS IN MILLIONS

	Fig. 3(a)	Fig. 3(b)	Fig. 5(a)	Fig. 5(b)	Fig. 6
Nodes	29,612	4,683	2,884	2,267	2,205
Edges	101,101	5,081	3,537	1,712	3,051
Degree	6.83	1.09	2.45	0.755	2.77
Trade, #	247,554	7,600	4,719	2,896	4,205
Avg.Trade	8.36	1.62	1.63	1.28	1.90
Diameter	22	7	7	4	7
Paths, #	207.48M	25,401	22,504	1,956	21,870
Length	6.51	2.45	2.51	1.15	2.54
Money	\$100,593	\$62,526	\$62,526	0	\$58,391

F. "Wealth Distribution"

The free money network comprises only 9.7% (2,884 out of 29,612) and 1.9% (4,719 out of 252,859) of all characters and transactions in the entire trade network. However, we found that the free money network also accounts for 62.2% of the total transaction money during the observed period (\$62,526 out of a total of \$100,593 when converted to US\$ using the proper conversion rates).

From Table III, we find that the free money and/or item network has a lower degree and shorter length than the entire trade networks because users in these malicious networks usually trade with other members in the same workshop and do not interact with other normal users.

The average number of trade per users of a malicious network is much lower than that of the entire network. This indicates that the users in a gold farming network do not trade frequently, and this results in a small network. However, this corresponds to more than 50% of the value of the entire trades. Comparing the columns for Figs. 5(a) and 6, we found that the network size of the free money network does not decrease significantly when we consider the over three-tier networks. Most of the free money trades follow the over three-tier pattern of Fig. 6.

To summarize, in order to extract the GFG utilizing basic analysis features, we first explored the trade network following the steps shown in Fig. 7. First, we extract the free money network from the entire network to remove the benign users

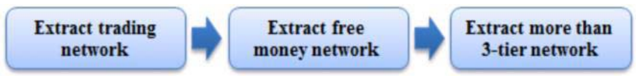


Fig. 7. Steps of trading network analysis.

mostly associated with free item transactions. Then we utilize the logic of GFG economics to construct a three-tier graph that includes only those nodes highly likely to be associated with the GFG.

G. GFG Detection

To provide further evidence on our manual identification of seeds, we checked whether these users have been detected and banned by the game company. Even though the company does not have sufficient information on GFGs as groups, it provides information on when GFG members use game bots, are involved in financial fraud or hide their connection information, and then ban those users. Thus, we check whether our manually detected users have been listed in the banning list and the company confirms that those users are banned. Additionally, we check whether detected users from our rules make any appeal to banning. Decisions by the company are contested, which may result in rolling back the banning decision.

In order to detect GFGs within the trading network, we develop a set of strict rules that can be used to ensure maximum (100%) accuracy in detecting seed characters for GFG detection. We base our rules on a thorough examination of the abnormal trading patterns and graph properties of abnormal characters in the trade network.

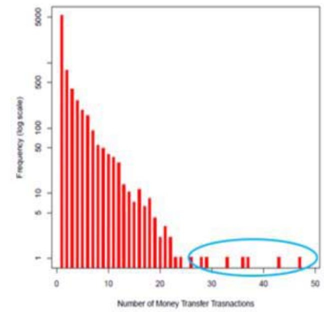
We examine the features of rules thoroughly and set up the threshold values to classify GFG members and normal users.

To develop the strict detection rules, we use the empirical background and acceptable (contrary to abnormal) behaviors of characters in this game. We use such behavior characterization to construct a set of heuristics for features associated with each character by type: gold farmer, banker, and merchant. In this step, we compromised the recall to maximize the reliability and develop the strict detection rules.

H. Transaction Patterns and Behavior Features

To detect abnormality in the GFG trading patterns, we first perform a screening test through the transaction behavior analysis. Through this analysis, we found that characters with less than 30 transactions include normal users found through manual inspection, as shown in Fig. 8.

We expanded the trade network of the top three suspicious characters. Then, we perform the analysis in the expanded network. We examine the characters who are within two tiers from the initially detected ones. Through manual separation based on the rules, we observe that there are 15 bankers, 92 gold farmers, and 71 normal characters. The game company confirmed that all detected bankers and gold farmers are classified as real GFG members by a long period of manual inspection and observation by monitoring professionals.



character id	transactions	description
287726	48	banker
23037	44	gold farmer
426943	38	banker
207567	37	gold farmer
427083	34	gold farmer
422555	30	normal user
400767	29	normal user
33788	27	gold farmer
135242	25	normal user

Fig. 8. Number of transactions (left) and manual inspection results (right).

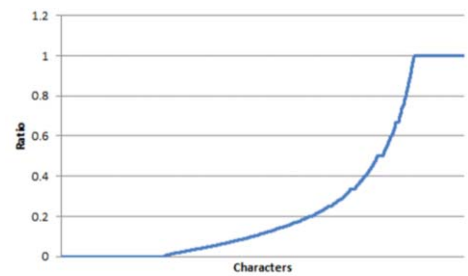


Fig. 9. Free money ratio distribution.

For rule generation, we extracted the features of GFG members by types. The extracted features include the player-level, the number of peer-to-peer trades, the number of agent trades, the number of individual store trade, the total game money gained, the total game money spent, the number of free item (given or taken, separately), the number of free money (given or taken, separately), the amount of free money and item (given or taken, separately), the total number of transactions, the number of free transactions (money or item, or both), and free transactions as a ratio of total transactions. Among those integrated features, the free money ratio was found to be the most significant to classify GFG roles. On the trade network expanded from the top three suspicious characters in terms of transaction frequency, we found that the free money ratio is at least 0.8 for gold farmers and at least 0.95 for bankers or merchants. The distribution of the free money ratio is in Fig. 9.

The second analysis metric we utilize is the amount of free money. By studying the cumulative distribution function (CDF) of the game money shown in Fig. 10, we found some characters who trade extremely large amounts of game money. We also performed manual inspection of them to understand their nature; the results are listed in Table IV. First, we found that those users who spend game money without gaining anything back are suspicious because this is counter-intuitive to market rules. Second, we found that those characters are bankers when the ratio of free transactions equals one.

I. Graph Properties in Trade Networks

To obtain discriminating features for members based on their roles, we also examine the graph properties of the trade network. First, we generated the refined gold farming network

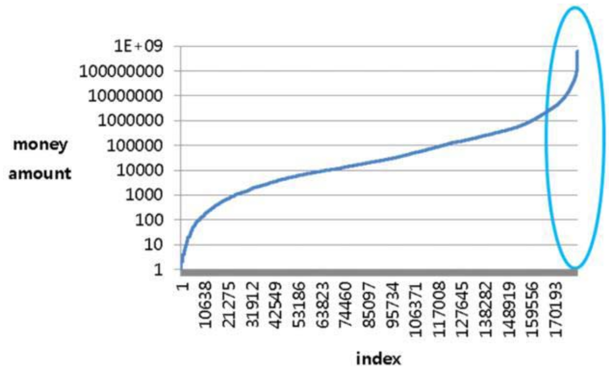
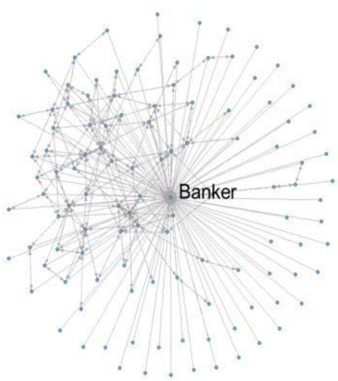


Fig. 10. Amount of game money.

TABLE IV
MANUAL INSPECTION RESULTS ON GAME MONEY ANOMALY

character ID	totalMoney Gain	totalMoneySpend	ratio	class
166521	0	2,125,000,000	1.00	Banker
400769	0	2,113,143,391	1.00	Banker
306145	30,733,000	2,080,703,064	0.21	Normal
374858	0	2,065,300,000	1.00	Banker
364623	23,464,999	2,052,696,321	0.00	Normal
342449	0	2,050,000,000	1.00	Banker
360886	60,151,500	2,046,483,269	0.14	Normal
383786	81,967,900	2,031,282,998	0.04	Normal
389035	0	2,027,000,000	1.00	Banker
302744	0	2,018,916,297	1.00	Banker



Description	Values
Avg. Degree	3.307
Avg. Weighted Degree	3.307
Network Diameter	8
Graph Density	0.029
Avg. Clustering Coefficient	0.213
Avg. Path Length	3.074
# of shortest paths	4,541

Fig. 11. Two-tier graph from top three abnormal characters in terms of the number of transactions.

with two-tier expansion from the top abnormal characters in terms of transaction frequency (the resulting graph is a three-tier graph). In the graph in Fig. 11, the character in the center is identified as a banker. Compared to the entire network, the graph density and average clustering coefficient are higher, indicating that the node-level topological properties could be useful for classifying the different roles of GFG members based on structural properties of GFGs. Network properties we extract are specified in Appendix.

Furthermore, we generated two-tier graphs from the selected bankers to obtain a larger graph, as shown in Fig. 12. Merchants have different positions from bankers. This implies that the graph properties of nodes in the trade network are important features to classify the roles of GFG members.

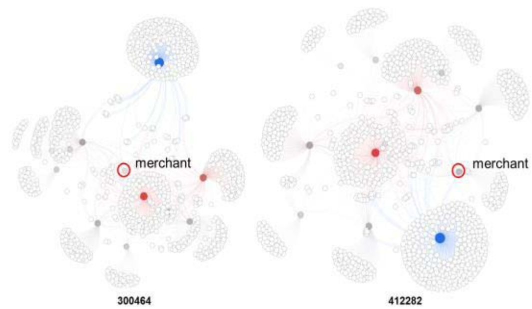


Fig. 12. Two-tier graph from initially detected bankers.

TABLE V
SETTINGS FOR BETWEENNESS CENTRALITY AND MANUAL INSPECTION RESULTS

Threshold	# of characters	Merchant
Greater than 0.001	228	N/A
Greater than 0.002	134	N/A
Greater than 0.003	95	N/A
Greater than 0.004	68	N/A
Greater than 0.005	58	N/A
Greater than 0.01	30	Partial
Greater than 0.02	18	N/A
Greater than 0.03	6	N/A

To examine the effect of the node properties of the trade network and detect the GFG, we explore the following topological properties: the clustering coefficient, closeness centrality, and betweenness centrality. The clustering coefficient denotes the number of triangles in the network, indicating that the connected ones of a character are likely to be connected to each other through an intermediary. This metric reveals how exclusive GFGs are compared to normal members in the trade network. The closeness centrality denotes how close a node is to others. It is inversely proportional to the sum of shortest paths to other nodes in the network. The betweenness centrality measures how many times a node is on the shortest paths that connect any two nodes in the network. This metric distinguishes the bankers or merchant characters who take the role of a bridge between GFGs and normal users.

Through our measurement, the betweenness centrality is shown to be the only useful measure for identifying character roles in the GFG. We hypothesize that the reason why betweenness centrality is important is that GFGs have unique characters of the banker and merchant, unlike normal users. The banker has role to connect GFGs and buyers, and the merchant connects the banker and gold farmers. Thus, their value of betweenness centrality will be higher. We investigated the characters with betweenness centrality over the threshold value by varying the value until the most interesting set of characters was identified, as shown in Table V. Some of the characters whose betweenness centrality ranges between 0.01 and 0.02 turned out to be merchant characters through the manual inspection.

J. Heuristic Rules

Based on the above characterization and findings, we formulate various role separation rules to identify characters. The separation rules (heuristics) are as follows.

TABLE VI
GFG From Detection Rules

Description	Values
Nodes	555
Edges	1,791
Network Diameter	8
Graph Density	0.006
Avg. Clustering Coefficient	0.334
Avg. Path Length	2.871

1) Gold Farmer: 1) Free trade ratio greater than 0.8. 2) Merchant (agent) trade equals zero. 3) Number of free trades (taken or given item and game money without reward) greater than 16. 4) Number of transactions per month is at least 20. 5) Amount of money is at least 5,000,000. 6) Level is at least 10.

2) Banker: 1) Free trade ratio greater than 0.95. 2) Merchant (agent) trade equal to zero. 3) Number of free trade (taken or given item and game money without reward) is greater than 3. 3) Number of transactions is at least 50. 4) Amount of money is greater than 2,000,000.

3) Merchant: 1) Betweenness centrality is at least 0.02. 2) Free trade ratio is at least 0.9. 3) Level is less than ten.

We built heuristic rules to detect GFG members with 100% confidence through a careful and systematic examination of users' trade behaviors in the absence of ground truth.

We confirmed that the company also recognized them as malicious users, and that detected users from our rules did not make any objection for banning.

In section V, we expand our detection method by employing other information to reveal more GFGs members.

V. GFG Detection: Results

Using the preliminary behavior features and detection rules developed in the previous section, we now explore the findings on GFG detection. First, we explore GFG detection using the rule-based method (in Section V.A). Then, we show how the (physical) network features can be further used to improve the detection results (in Section V.B).

A. Rule-Based Detection Results

Gold farming networks are detected using the rules included 9 merchants, 475 gold farmers, and 71 bankers-with network properties shown in Table VI. Among the 475 gold farmers, 246 farmers are newly created characters during the studied period. The detected GFGs are simply part of the entire GFG because we apply strict rules mainly built based on manual inspection. To identify entire GFGs, we need an automatic expanding method, and thus we perform the steps shown in Fig. 13. After we detect GFGs using the heuristic rules, we expand GFGs using the network IP address information used by GFGs, examine the trade log of detected ones, and finally refine the GFGs.

B. Physical Network-Based Detection Results

Because the machines in the same physical location often use the same physical network, their IP routing selects similar paths in the local networks, and the IP addresses in their routing paths are similar. We extract all related IP addresses that use the same network as the GFG from the strict rules. We match the first three upper classes from the IP address (by concentrating on 24 subnets). For example, the IP addresses related to IP address 1.1.1.1 encompass 1.1.1.∗. Then we extract all accounts that login from the extracted IP addresses. Next, we delete the unrelated characters who use the same network, but have no trade with the GFGs. We list a comparison between the initial group (network) and the final GFG group using this feature in Table VII. The initial GFGs consist of 555 characters, which increase to 2,811 using the network IP information. The refined GFGs compose 9.5% of the total.

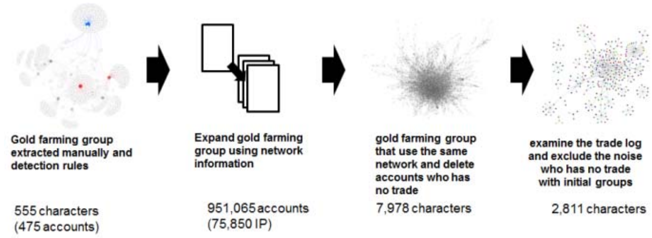


Fig. 13. The expanding procedure.

TABLE VII
Graph Properties of Entire and Final Groups: Clustering Coefficient and Path Length Are Average

Description	Entire network	GFG network
Nodes	29,612	2,811
Edges	101,101	6,031
Network Diameter	22	21
Graph Density	0.000	0.001
Clustering Coefficient	0.100	0.044
Path Length	6.51	6.683

Finally, we compare the graph property of the entire trade network, and detect the GFGs shown in Fig. 14 in terms of clustering coefficient, betweenness centrality, level, and free money ratio of the characters. Considering the clustering coefficient, we find that the GFGs have a skewed distribution, which implies that the GFG members have different roles.

Overall, the betweenness centrality of GFGs is higher than the entire network. We hypothesize that different roles have different ranges of betweenness centrality as well. By manually vetting characters with their betweenness centrality, we decide to exclude a few characters with an extremely high betweenness centrality because they are buyers who purchase items from several GFGs, and thus their topological position in the graph gives them a boost in their centrality values. By examining the character level as a feature, we find that GFG members have more low-level characters than the entire network. All GFG characters have a free money ratio over 0.4. The findings are shown to be useful for generating automatic detection rules. Once we build the ground truth with the strict rules and the network expanding method, we can build the automatic classifier.

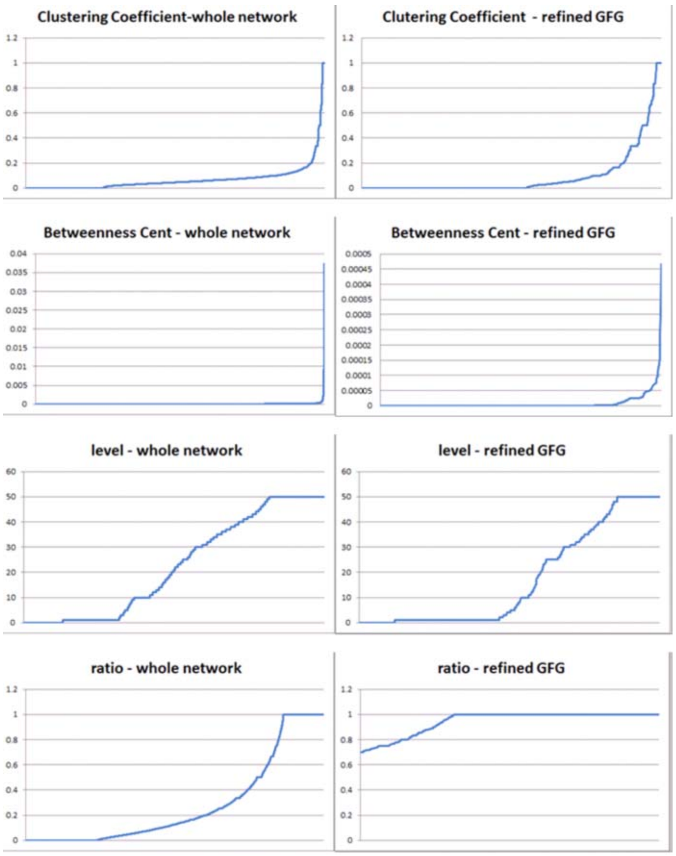


Fig. 14. Graph property for entire network (left panels) and GFGs (right panels). X-axis indicates the character index according to Y values.

VI. GFG Economic Scale

In the following we discuss the economic scale of GFGs; basic GFG economics and how massive banning efforts conducted by the game company affect the economic scale.

A. Basic Economic Characteristics

A rule-based method is used for classifying characters in a GFG by role. Earlier, game companies banned only gold farmers, but this banning policy had several side effects. As collateral damage, the strong banning policy caused identity theft because gold farmers created new accounts with others' identity after they were banned. Although the company banned gold farmer accounts, the damage to the GFGs was minimal because GFGs could create new gold farmers with negligible effort. However, if the game companies banned both gold farmers and banking characters, the GFGs could not run their business anymore because game money would be confiscated. To this end, we detected 3,725 gold farmers, 76 banking characters and 17 merchant characters by using the same method in Section IV and V. We expanded the analysis period from 1 month to 3 months to track dynamics of GFGs. Further, the gold farmers were revealed to be not only bot players as in the past but also manual gold farming players. Table VIII shows each role's statistics.

In total, we extracted 49 GFGs with the community detection method; visually shown in Fig. 15, whereas their characteristics across multiple features are listed in Table IX.

TABLE VIII

The Statistics of GFG Roles: Level, Transactions and Money Gain Are Average per Character. Real Money Is in US$

Role	Chars.	Level	Trans.	Gain (kina)	Money
Gold Farmers	3,725	35	33.82	230,786,815	$462
Bankers	76	1	9.36	823,699,242	$1,648
Merchant	17	10	29.9	1,275,823,122	$2,552

Fig. 15. Gold farming network separated by each GFG.

TABLE IX

GFG Information

	Nodes	Trans.	Edges	Game Money	US$
Mean	83	2,827	295	20,977,234,225	$41,954
Std.dev	95	2,852	316	12,044,804,616	$24,090
Max	590	11,637	1,964	53,699,776,093	$107,400
Min	6	168	13	6,171,466,805	$12,343

The community detection method divides GFGs into communities based on the network IP information. If GFG members who use the same band of IP addresses, they form a community. After extracting each GFG's information, we checked the correlation between the incoming game money and the node/transaction. In general, one would anticipate a positive correlation: if the node or transaction value is high, the amount of incoming game money is larger. However, we discovered no strong correlation between the incoming game money and per-node transactions, thus highlighting a potential bias in the income associated with some transactions. Fig. 16 and 17 show the total game money and per node transaction for each GFG according to GFG communities. In both figures, the X-axis is an index of the 49 GFGs detected using our method.

We note from the results in Table IX that there are various sizes of GFGs from 6 to 590. The small size of GFGs indicates the existence of groups running for a small gain or as a way to level-up their own game characters. Large GFGs indicate business grade GFGs. We also estimated their capital gain by that time using real money exchange ratio. The smallest GFG has more than 12,000 US$ worth of assets in a month, whereas the largest has more than 107,000 US$. If they steadily run the GFG, they can earn 1,284,000 US$ (not accounting for tax).

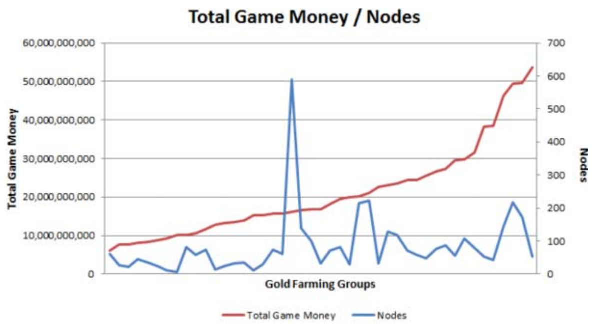


Fig. 16. Total game money and the number of nodes for each GFG.

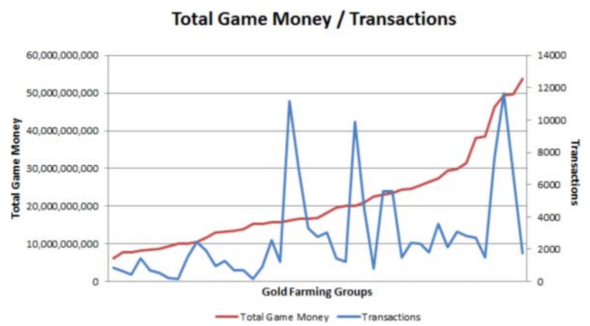


Fig. 17. Total game money and transactions for each GFG.

B. Temporal Dynamics and Banning Effects

Currently, GFGs have become sufficiently evolved to be able to discern the game companies' design, and have evolved their methods for farming and distributing the money. Such GFGs run expendable game accounts to conceal their controlling and banker accounts. In some cases, they form a point-organization very similar to crime organizations in the real world. Interestingly, they change the trade pattern and location of the money repository in response to the banning operations initiated by the game companies. In addition, they change and reform the network structure after the banning operation occurs to recover the damage. Based on the related works [10], [15], long-time observation has been performed to monitor the dynamics of GFG trade networks, especially the free-money-trade and item-trade networks. We observed changes in the economic activities, structure, and behavior of GFGs after the banning operations; there were totally ten banning operations in 12 weeks of observation.

In the following paragraphs, we observe closer the dynamics of GFGs considering the company's reaction to GFGs and banning efforts. The AION operator performed several aggressive banning efforts, notwithstanding the profit damage caused by such effort. Table X lists a summary of the number of banned characters, the number of GFG banned members, the number of newly added GFG members, the total number of transactions issued by banned members, and their share of the ecosystem (confiscated by the operator). The counts are produced weekly. From this table, we aim to draw conclusions on 1) how effective are the procedures employed by the operator in blocking GFGs, 2) how capable GFG operators are of recovering after a major banning operation.

We found that GFGs are supplemented with new members immediately after the large-scale banning operation.

TABLE X

BANNING EFFECTS ON GFG DYNAMICS. TOTAL ECONOMIC SCALE IS IN HUNDRED BILLIONS ($\times 10^{11}$)

Weeks	Banned characters	GFG members	New GFG members	Total economic scale	# of transactions
1	13,378	2,772	0	1.51	12,607
2	0	2,716	132	1.47	12,667
3	14,778	2,729	77	1.45	12,124
4	0	2,871	113	1.49	13,196
5	15,366	2,659	109	1.47	12,067
6	13,418	2,683	97	1.42	11,302
7	9,130	2,127	25	1.32	10,905
8	7,286	1,294	36	1.11	6,345
9	352	1,644	89	1.17	6,963
10	2,159	1,845	138	1.29	7,197
11	6,249	2,008	126	1.32	7,733
12	1,487	2,140	104	1.50	5,785

Interestingly, some GFGs control their business extension temporarily by hibernating, and then resume employing new characters after a large-scale banning operation. When tracking the number of GFG members, we found that the banning operation is effective for reducing GFG size, but not for eliminating all GFG members or their assets. While the economic scale of the GFGs decreases slightly after large-scale banning operations, the number of transactions in the entire game significantly deceases. We theorize that GFGs attempt to conceal abnormal behavior to avoid banning. This implies that the GFG economy behavior could change in response to the company's policy.

From Table IX, we can draw several interesting conclusions that answer the two questions we set earlier. First, the newly created GFG members are approximately 100 any week, whereas the number of banned GFG characters is usually over 2,000 (with the exception of weeks 8, 9, and 10). This highlights the nature of this underground world: 1) accounts utilized for gold farming are sometimes stolen, and are not created by the GFG, 2) the GFG plans for banning events in advance by registering accounts in bulk, and operates them in a stealthy mode until required in active participation. The same insight is used to answer the second question: GFGs quickly recover after a large operation.

The week-over-week banning results in confiscating much game money, thus highlighting the profitable nature of the game to GFGs operators. The fact that not all their resources are confiscated encourages GFG operators to pursue their activities by utilizing techniques to thwart detection.

As a result, the game operator has recently been using selective banning, but targeting bankers only. To that end, although the number of banned characters has been greatly reduced, the total number of confiscated assets and game money has increased significantly. The approach proposed in this work guided the banning activity, and indirectly disincentivized GFG operators.

C. Evaluation

Some GFGs operate with gold farmers that use game bots. However, they are easily detected and banned by game companies because the programmed actions of the game bots are noticeable. Some GFGs operate with human gold farmers to evade being detected by the game companies. Such GFGs hire cheap laborers and make them play games as game bots. Human gold farmers are difficult to detect and ban because they do not violate game laws. However, they play the games for much longer than normal players do. Without sufficient evidence, game companies cannot extract information from the GFGs o represent and correspond to solid ground truth. As a result, the detection of GFGs is a challenging issue for game companies.

In the absence of ground truth, we evaluated our proposed method in an alternative way by leveraging the banning list. We tested our method in detecting game bots even if it does not constitute an entire GFG. From the banning list, we randomly selected several characters as seeds and applied the same method to expand them. By applying rule-based detection, we extracted 599 characters. With the expansion that uses the physical network feature, we extracted 692 characters, and 601 characters were checked from the list as being banned. The detection accuracy of our method is 86.85%, which is reasonably operational.

VII. Conclusion

We proposed a framework for detecting GFGs using trading network analysis and a rule-based detection method. The framework has the following merits to control GFGs:

a) It detects only GFG characters without normal players.

b) It separates each GFG. If a game company quickly realizes that a GFG has become sufficiently big to break the game balance, the game company can take proper actions on time.

c) It classifies GFG characters by role. This allows the achievement of maximum efficiency at minimum banning, similar to surgical strike. Because having a gold farmer player is profitable for a game company, it needs to minimize banning while maximizing damages to GFGs.

As a result, the game company can control GFGs with our framework more efficiently. This approach detects anomalies in trade patterns, and thus it can be applied to other game genres with economic functions, including trades between users. For future work, we will determine the feature that is important for GFG growth. Furthermore, according to such growth, we will design the optimum time measurement for banning GFG.

Acknowledgement

The authors would like to express our sincere gratitude to NCSoft Inc. for providing data for this work.

Appendix

A network (graph) is a set of items, called nodes, with connections between them, called edges [19].

$$\mathrm{G} = (\mathrm{N}, \mathrm{E})$$
$$N \text{ is the set of nodes}$$
$$E \text{ is the set of edges}$$

In this paper we use this network (graph) formulation to represent various activities in the online game, including free money and free money transfer transactions, actual transactions, etc. We further use such graphs for identifying GFGs (c.f. section IV) using some of the graph theoretic measures below.

Average degree is the average of the edges of a node of a graph. High average degrees means numerous trades for that character.

$$\mathrm{d} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{n}} \mathrm{deg(i)}}{\mathrm{n}}$$
$$deg(i): \textit{the number of links (degrees) connected to node } i,$$
$$n: \textit{the number of nodes in the network}$$

Network diameter is the maximum distance between any pair of nodes. This is used to summarize distances between nodes in a graph [20].

Network density is defined as the number of edges out of the possible edges, all possible pairs of nodes. It is expressed as proportion between 0-1 [21].

$$\mathrm{d} = \frac{|E|}{2n(n+1)}$$

Clustering coefficient is defined as the probability that two neighbors of a node are themselves neighbors. Intuitively, this represents the relative abundance of triangles in networks [19].

$$\mathrm{C} = \frac{6 \times \textit{number of trianlges in the network}}{\textit{number of path of length two}}$$

Average path length is defined as the average geodesic distance between all pairs of nodes [19].

$$l = \frac{1}{\frac{1}{2}n(n+1)} \sum_{i \geq i} d(i,j),$$
$$d(i,j)_j: \textit{the geodesic (shortest) distance between node } i \textit{ and } j.$$

Closeness centrality is the reciprocal of farness, which is the sum of geodesic distance from node i to all other nodes [19].

$$\mathbf{c_k} = \frac{1}{\sum_j d(k,j)}$$

Betweenness centrality is the number of times that a node lies along the shortest path between two others [19].

$$b_k = \sum_{i,j} \frac{g_{ikj}}{g_{ij}}$$

g_{ikj}*: the geodesic(shortest) path between node i and j that passes node k.*

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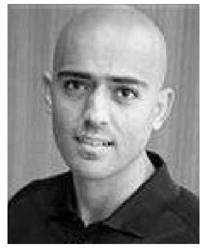

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