Illicit Bits: Detecting and Analyzing Contraband Networks in Massively Multiplayer Online Games

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Abstract — **Although trade in illicit items and services is prevalent in many economic systems, collecting reliable data and making empirical claims about this activity is difficult. Using anonymized behavioral logs from a massively multiplayer online game, we analyze the items exchanged by players later banned for gold farming. We simultaneously analyze clandestine social networks of deviant players in MMOGs as well the network of contraband items that are sold by these players. The insights from the network analysis are used to build predictive models for identifying deviant players in the clandestine networks. We show that the results obtained from our proposed approach are far superior to the state of the art for such clandestine networks. Additionally we observed that the contraband networks contain certain type of objects which are not found in their "normal" counterparts.**

Keywords- contraband network, gold farm, clandestine network, massively multiplayer online game, multiple consignment contraband.

I. Introduction

Contraband are illegally obtained items constituting a parallel or shadow economy which evade regulation or taxation. Although governments have a compelling interest to interrupt these exchanges, especially when they involve dangerous or harmful items like weapons or drugs, knowledge about how trafficking rings are structured or evolve is often *ad hoc* and anecdotal because it is necessarily difficult to collect information about clandestine organizations. Just as the smuggling of contraband has plagued governments since time immemorial, contraband has likewise appeared within socio-technical systems like virtual worlds such as massively multiplayer online games (MMOGs) in the form of illicitly exchanges of virtual wealth and items for real, offline currency.

If the organization of contraband trafficking operations follow similar demands and constraints online as they do offline, analyzing the structures and dynamics in one context can be mapped to other contexts [1]. Given the difficulties of obtaining data about traditional clandestine organizations, we use anonymized digital trace behavioral data from an MMOG to analyze the in-game items traded by users engaged in illicit activity. This exhaustive data, the unobtrusive way in which it was obtained, and the extent to which online behaviors are similarly motivated and constrained suggests using MMOGs can provide a test bed for both empirically testing theories about social and organizational behavior and developing methods such as improving the detection of clandestine activity. Previous work has suggested that the properties of clandestine networks in a MMOG are created by processes that are similar to those exhibited by drug trafficking networks [2, 3].

The exchange of contraband items between game users can be modeled as networks of the items and actors. First, we recognize that multiple types of actors exist as well as multiple dimensions of interactions which bind actors together; second, that these networks are structured by processes occurring at multiple levels of analysis; and third, that these processes and networks can change over time [4-6]. Next, we employ

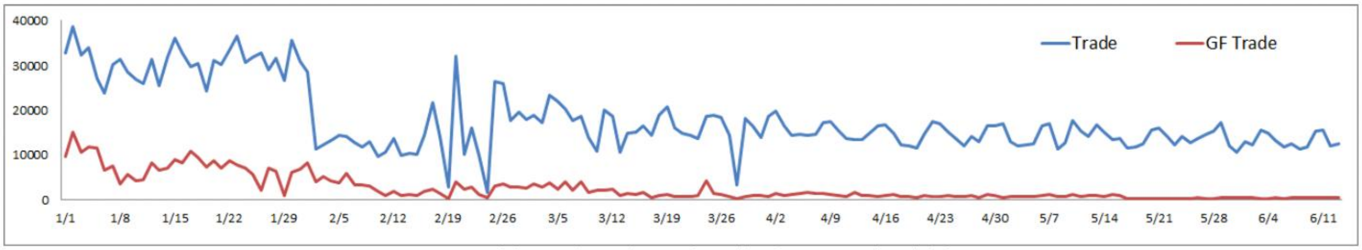

Figure 1. Weekly trade volume for all players and gold farmers

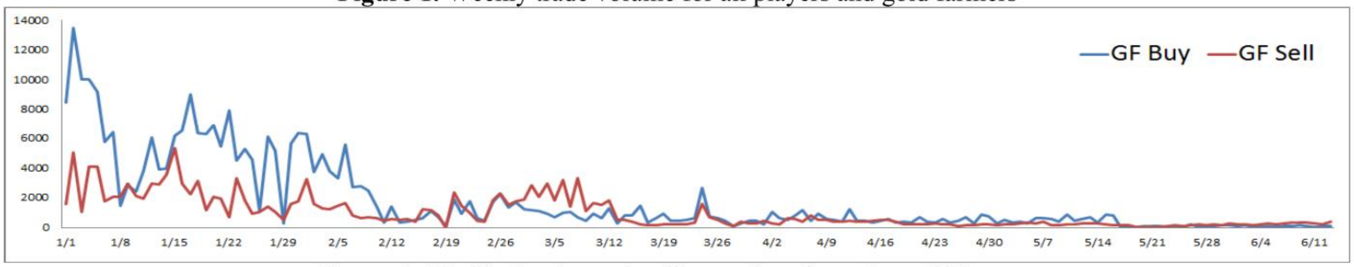

Figure 2. Weekly buying and selling trade volume for gold farmers

network analytic metrics of the relationships among contraband items as predictive features for machine learning methods. These behavioral models of contraband item use and exchange are associated with individuals engaged in clandestine activity. Finally, we integrate these contraband item models with other behavioral features to improve upon existing prediction approaches [7]. We conclude by discussing the implications this approach has for understanding the general processes which support clandestine organizations and directions for future methodological development and research.

II. Related Work

The problem of smuggling and contraband is as old as the establishment of formal trade relationships between nations. It plagued England after the establishment of a national customs collection system in 1275 [8]. Williams [9] gives a historical overview of the problem of smuggling and contraband and notes that in the medieval era smuggling was mainly focused on highly taxed and sought-after export goods. Interestingly, we observe a similar phenomenon in the massively multiplayer online game EverQuest II (EQII), as described in Section IV. A comprehensive historical survey of smuggling and contrabands by Karras [10] describes the relationship between the recognized trade and the "shadow" economy which constitutes smuggling. Karras finds also that the combination of corrupt officials and smugglers in some cases actually eased the life of local residents in different countries during the imperial era.

The inherent obstacle in studying smuggling is the extreme difficulty in collecting data in this domain, and thus there are not many such studies which use empirical data. There are, however, a few notable examples e.g., Von Lampe [11], who assessed the black market of cigarettes in Europe based on the open source data available on the subject, and the Caviar network data of Morselli [12]. The literature on contraband also notes that, while generally only one type of contraband item is transported at a time, there is mounting evidence that a large volume of contraband follows the Multiple Consignment Contraband (MCC) method which is based on the idea that multiple contrabands are shipped together in consignments. Within the computer science domain, the literature about contraband is mainly focused on using computing techniques for enabling the discovery of contraband in the real world or in contraband digital files. Shrader et al [13] describe a digital forensic tool for the identification and tracking of contraband digital files shared via the BitTorrent protocol.

An important component of studying illicit trade and contraband in any domain is the study of the social networks of the smugglers and the clandestine actors themselves. Ahmad et al [7] describe the use of machine learning approaches for identifying gold farmers, the players who stockpile in-game wealth and goods in order to sell them to other players for real money. Keegan et al [2] and Ahmad et al [14] studied the clandestine trade and trust networks of gold farmers respectively and described how the gold farmers try to obfuscate their interaction patterns in these networks to evade detection. Also relevant is the study of recommendations in co-extensive networks in MMOGs by Ahmad et al [15] which describes the relationship between item trade and social relationships in MMOGs. Lastly, Keegan et al [3] discuss the usefulness of studying clandestine networks in virtual worlds and their applications to studying their counterparts in the offline world.

III. Legal vs. Illicit Trade Activity in MMOGs

Trade is an important an integral activity in most MMOGs and serves a variety of purposes e.g., buying new items to improve one's character, raw materials to craft new items, materials to repair equipment etc. We use data from one PVE (Player vs. Environment) server in EQII called the 'Guk' server. The data that we use spans from January 1 to June 11, 2006. We only consider the players who were involved in trade activities in this period which contains 7,652 players and out of these 251 are gold farmers. We note, however, that the number of active gold farmers changes over time partially because the identification of these players as gold farmers resulted in the removal of these accounts from the game. We define an item to be contraband not by an intrinsic property of the item but

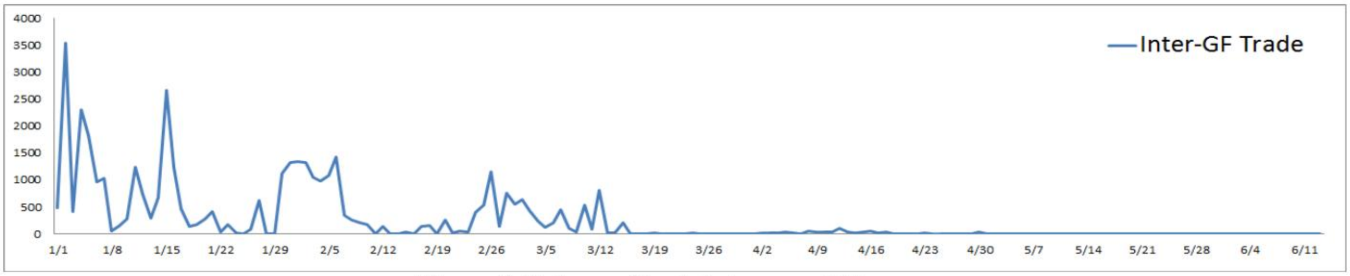

Figure 3. Volume of trade between gold farmers

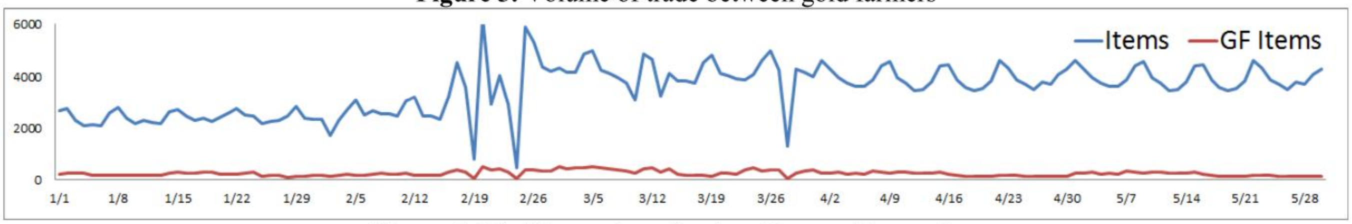

Figure 4. Weekly number of unique items sold over time

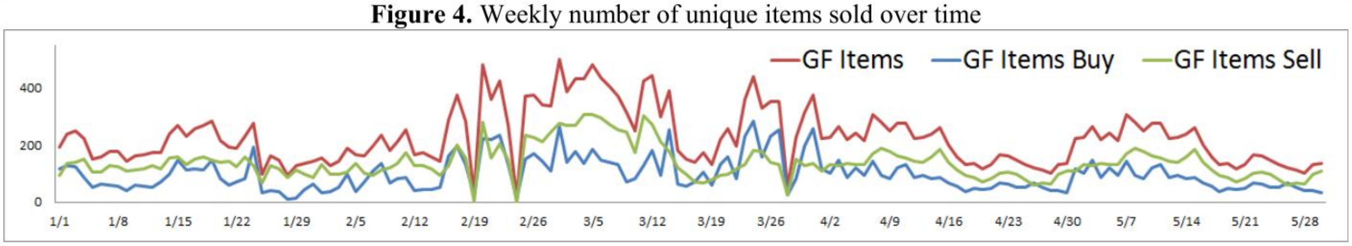

Figure 5. Weekly number of unique items, bought and sold over time by gold farmers

rather if the item was sold by a player identified as a gold farmer. Gold farming activity and consequently contraband sold either varies over the course of time or eludes detection after a certain point in time. Figure 1 shows the volume of trading activity as measured by the number of transactions over time on a weekly basis. It is clear that gold farmer trading activity is a significant fraction of the trading activity for the first two months and then significantly declines. There are several possible explanations for this: Gold farming activity declined within this server as a result of changes in market demand, administrator enforcement, or practices employed by the gold farmers to evade detection[2]. There is however insufficient data to decide which possibility is the correct one. Also noteworthy is the overall trading activity exhibits regular periodicity beginning in March. The peaks correspond to increases in trading activity on weekends over weekday activity.

Since the main revenue generation activity of gold famers is by selling their “loot” or the result of their efforts to other players, we also compared how the buying activity of gold farmers compares with selling activity as given in Figure 2. Surprisingly, a larger volume of trading activity of gold farmers is for buying items instead of selling them. This implies that gold farmers may be buying items for some other purpose. We explore this in more detail in the next section. Previous work on gold farming [2] has indicated that the gold farmers may be trading with one another in order to confuse the game administrators and evade detection. To explore this further we plotted the volume of trade between gold farmers as given in Figure 3. Here we do not see any discernable patterns but the trade volume declines to nearly zero after March and is never a significant proportion of the total gold farmer trading activity.

The trading volume measured in terms of transactions declines over time and becomes increasingly periodic; however, the number of items which are traded, as shown in Figure 4, indicates a different type of behavior when it comes to gold farmers. The number of unique items sold shows periodic behavior for most of the span of the data, with the exception of a phase shift in February. Interestingly, even though the trade volume of items sold by gold farmers changes over time, the number of items remains more or less constant. This implies gold farmers are interested in certain types of unique items, a phenomenon which is discussed in more detail

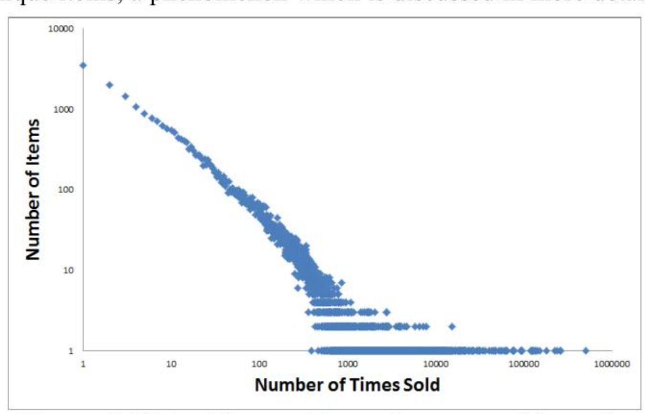

Figure. 6. Dist. of items sold over the course of 5 months

in the next section. Figure 5 gives a more detailed breakdown of gold farmer items. There are some major differences with respect to the number of unique items which are bought or sold by gold farmers e.g., the number of unique items which are sold by gold farmers, or contraband, are more than the number of items which are bought by gold farmers even though the reverse is observed when we look at the trade volume for the gold farmers. This implies that the gold farmers are buying many items in bulk but sell items to other players in smaller portions.

IV. CLANDESTINE SOCIAL NETWORKS AND ILLICIT TRADE IN MMOGS

Previous work on the trade networks of gold farmers [2] has concentrated on only the transaction networks without considering the items that are traded. Here we extend the previous work on this area by concentrating on the contraband items in the data.

4.1 Item Projection Networks

Consider the bipartite (two-mode) network consisting of the social network of market actors (buyers and sellers) in one mode and the items that they trade in the second mode. We project this network into a unipartite (one-mode) space of relationships connecting items only if they have been traded by the same person. This network reveals whether pairs of items are regularly exchanged by many players.

Table 1 gives the summary of the item network over the course of five months. We also consider a "gold farmer (GF) subnetwork" of items which are traded by gold farmers. Since there are a large number of items which can be traded by a player, the item network can be very dense. Comparing the general item network to the gold farmer network, we see that both networks have similar densities. While this suggests that gold farming activity is difficult to discern from licit in-game economic, we also note that gold farmers trade in a relatively small number of items as compared to the rest of the population. As shown in Figure 6, total activity for all items in the network follows a long-tailed distribution with most items being exchanged few times but a few items constituting the vast majority of trading activity.

Now, we consider the items which are sold or bought more often by gold farmers than the rest of the players. We examine items which are not only frequently sold but also frequently bought by gold farmers. Tables 2 and 3 respectively report a list of the top 5 items frequently bought and sold by gold farmers. We define Support of an item *X* as the number of transactions where the item occurs divided by the total number of transactions. One interesting characteristic of the items frequently bought by gold farmers is that these are usually low-end items, i.e. items that are cheap to buy and, in many instances, used for crafting other items. Gold farmers could also be using these items to craft more complex items to be sold later.

One possible explanation for this phenomenon is that gold farmers may be hoarding some materials in order to monopolize the production of certain items in the game. On the other hand, the items which are sold almost exclusively by gold farmers have a very different characteristic: these are almost always high-end items which require a lot of in-game effort to obtain or craft. This makes sense from the domain perspective since the gold farmers would mainly be interested in selling items which are likely to yield a higher payoff as compared to more generic items within the game.

Table 2. The top 5 items, bought by gold farmers

Item Name	Number of Transactions	Support
Repair materials	3898	0.81
Aerated mineral water	3,611	0.99
Mulberry	2,273	0.53
Bees wax candle	1,173	1.0
Crude solidified Enneanoid Loam	201	1.0

Table 3. The top 5 contraband items, sold by gold farmers

Item Name	Number of Transactions	Support
Ebon Relic	6,417	0.70
Star Sapphire Amulet	5,478	0.68
Indicolite Relic	5,000	0.67
Star Sapphire Scrying Stone	4,971	0.70
Bayberry Sealed Document	3,964	0.71

4.2 Frequent pattern mining analysis

We improve upon this analysis by doing frequent pattern mining analysis to determine what items are sold together by gold farmers, using an adaption of the Association Rule Mining framework [16]. The concept of Support as described previously is useful here since we are only interested in the items that are sold almost solely by gold farmers, the Confidence of an item, from the frequent mining paradigm [16], is a less useful concept since there are a large number of items which have extremely low support, e.g. only ten transactions out of 28 million. The inclusion of such items in

Table 1. Characteristics of the item network over time

Mon.	*Edges*	*Nodes*	*d*	$Edges_{GF}$	$Nodes_{GF}$	d_{GF}
Jan	3,489,037	13,009	0.041	76,559	1,874	0.044
Feb	4,392,985	16,543	0.032	83,998	2,432	0.028
Mar	7,539,607	29,998	0.017	180,348	3,369	0.032
Apr	7,033,935	18,568	0.041	77,428	2,011	0.038
May	7,755,564	19,012	0.043	81,758	1,436	0.079

the analysis is important since such items are usually high end items as described previously and thus require some time to accumulate. We can, however, specify a threshold in terms of the least number of transactions τ that must be present in dataset. Once we have identified the items which have high Support amongst gold farmers these can be used as features to predict gold farmers as we demonstrate in section 5. Since we are only interested in the item sets which have high support amongst the gold famers, item set generation can take this into account by only generating the frequent item sets which have a minimum support amongst the gold farmers.

It should be noted that there is one shortcoming that must be addressed in the interpretation of these results. Since the gold farmers studied are only the ones who were identified, there are certainly players who are gold farmers but had not been identified [7]. Consequently, this affects the support of the item sets bought or sold by the gold farmers. Previous work [2] has established that a substantial subset of the people who trade with gold farmers, called gold farmer affiliates, may be gold famers themselves. We thus refine the support metric to include the cases where the items were bought or sold by gold farmers. Thus the *Auxiliary Support o*f an item is defined as the proportions of items which are sold by gold farmers and the gold farmer affiliates with respect to the total number of transactions involving that item. This, however, dramatically changes the number of items under consideration since many of the gold farmer affiliates are prolific buyers and sellers. Thus in January there are 1,874 items associated with gold farmers but 3,998 (more than twice as many) items associated with the affiliates. An analysis of the types of items associated with the affiliates paints a more complex picture – the gold farmer in-affiliates i.e., players who buy items from gold farmers, usually buy high-end expensive items from them while the gold farmer out-affiliates usually buy a combination of all types of items so that it is difficult to categorize them.

4.2 Frequent-Networks of Contraband in MMOGs

Just as there are certain items which are frequently associated with gold farmers, there are also certain groups of items which are almost always sold by some gold farmers but not at the same time e.g., consider items A and B which are sold together by gold farmers and item C which is also sold by the same gold farmers but at a later time. While market basket analysis can be used to determine the groupings of items which are sold together frequently, the traditional framework of market basket has to be modified in order to discover grouping of items which are separated across time but which are nonetheless sold by gold famers. It should be noted that this problem is different from sequential pattern mining because we are not interested in the sequence or the order in which the item is sold or bought but if certain items are likely to be bought or sold by the same group of people over the course of many transactions. Thus, it is possible to construct a network of such items, which we call the frequent-network of contraband in MMOGs. Raeder et al [17] introduce the concept of market basket analysis with network data. We use a different framework from that used by Raeder et al [17] since the purpose of our analysis is not to discover network based association rules for all the transactions but to discover frequent patterns of networks of items which are associated with gold farmers or their affiliates. An example of the network of items [15] with the largest support is given in Figure 8.

We used the association rule mining framework for this task as well; the algorithm given below describes the candidate generation and evaluation task. First only the items which have the minimum Support amongst the gold farmer class are generated. Once such item sets have been generated, a levelwise generation of more candidate sets can be done in a manner similar to the Apriori algorithm [16] by generating new item sets by concatenating the item for an item set by an item set of size one but for only those cases where the support is greater than or equal to the minimum support. Once all such itemsets have been generated, the network of itemsets can now be generated. Since the networks of items that we want to extract are not necessarily present in the same set of transactions, we have to define the concept of support in a different manner. Given an itemset consisting of *k* items we represent it as a *k*-complete graph N_S. Now consider the social network of people who have traded with this item, for all the frequent items associated with these people we generate new itemsets by the union of the previous graph N_S and itemsets which have at least one element common with N_S. The support for the network graphs is defined differently because of the network effect. Additionally we introduce the idea of *background support* - the proportion of people who are common to both itemsets i.e., the number of people who have either bought or sold that item. Thus given two item- networks represented as graphs N_A and N_B having one or more elements (represented by set N_C) common between them, the support of the two elements is the number of transactions where either of these two itemsets are observed with the class of interest (gold farmers in the current domain) in the dataset divided by the total number of transactions where these instances are observed. This can be illustrated by considering graph G_{AB} in Figure 7, itemset *C* is associated with a subset of the same people who are associated with G_{AB}.

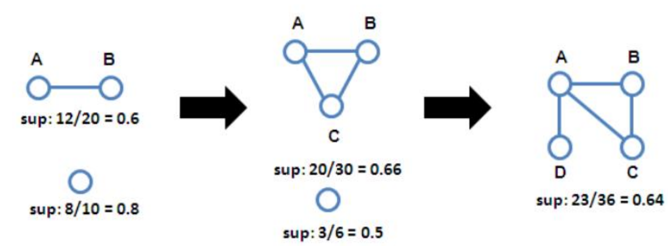

Figure. 7. Constructing frequent-networks of contraband items

The item sets are lexicographically arranged and since the graphs are generated from these graphs, the network of items are generated lexicographically as well which avoids the problem of having to check for isomorphism between different graphs.

```
Discover Frequent Item Networks
Input: Transaction database T, Minimum
Support minSupp
       Maximum size of the network graph
maxNetSize
       The background support backSup
I(j), itemset at level j
  begin
    For each Transaction;
       Save counts C_j and counts C_jGF
        for all the itemsets j in the set
I(1)
    Save the itemsets I_j where C_j / C_jGF ≥
minSupp
    Set j = 1
    While sup_GF(I(j)) ≥ minSupp
       Generate I(j+1) = I(j)+ I(1), j = j+1
    Set N(1) = I(1)
    While sup(N(j)) ≥ minSupp and j <
maxNetSize
       Generate N(j+1) = N(j)+ N(j-1), j = j
+ 1
        sup(N(j+1)) =
(C_GF(j)+C_GF(j+1))/(C(j)+C(j+1))

  end.
```

Algorithm 1: Generating the frequent Item Network

The main idea behind the approach of using not only item sets but also networks of item sets is that if one can discover such groups of items then they can be used to enhance gold farmer prediction methods. In this case, a feature would constitute a graph of frequently sold items instead of features which are just counts of scalars using the count of items themselves. Figure 9 illustrates this approach where the feature sets consist of a network of frequently occurring items.

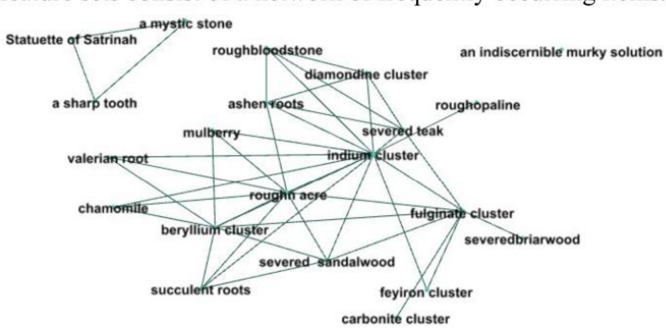

Figure. 8. Network of Items with more than half a million transactions

V. Contraband Based Prediction in Clandestine Networks

We now demonstrate the utility of using contraband and contraband-networks as features in machine learning models for predicting if a player is a gold farmer or not.

A. Datset

The timespan that we consider is five and a half months as described previously. We limit the set of players under consideration to those who have traded at least once and exclude players who have engaged in other forms of "trade" like gifting or bartering. Thus there are 9,383 players, and out of these, there are 331 are gold farmers. There are also 5,650 gold farmer affiliates, i.e. players that gold farmers have traded with. 4,497 players sold items to gold farmers and 4,136 players bought items from gold farmers. This implies not only that the gold farmers are prolific traders but also that the gold farmers trade with a large set of same traders.

B. Model Descriptions

Using the consignment trade data, we constructed a set of machine learning models using the item sets, their networks, player demographics and in-game characteristics as features. The last two feature sets correspond to the features used in the previously reported results on gold farmer detection [7]. Using a combination of these features and also considering them in isolation, we describe the following four models which were to address the current classification problem:

- **Model 1 (Player Attribute Based Features):** These features are based on the attributes of the player's character in the game e.g., character race, character gender, distribution of gaming activities etc. These are the same features which were used by Ahmad et al [7].
- **Model 2 (Item Based Features):** These are the features which are derived from items bought and sold from the consignment network. These features are based on the frequency of the frequent items sold or bought by gold farmers.
- **Model 3 (Player Attribute & Item Based Features):** All the attributes from the previous two models.
- **Model 4 (Item Network Based Features):** Features which are derived from the item network in a manner analogous to Model 2.
- **Model 5 (Player Attribute & Item-Network Based Features):** A combination of features from Model 1 and Model 4.
- **Model 6 (Item Network & Item-Network Based Features):** A combination of features from Model 2 and Model 4.
- **Model 7 (Player Attribute, Item & Item-Network Based Features):** Union of all the features described above.

C. Experiments and Results

We used a set of standard classifiers for the classification task using the Machine Learning package Weka [18]. The classifiers that we used are as follows: Naive Bayes, Bayes Net, Logistic Regression, KNN, J48, JRip, AdaBoost and SMO. The results of the predictions from the various models are given in Table 4 where the models correspond to the models described in the previous section. We only report results from the best classifier for each model instead of giving results for all the classifiers mainly because of space constraints. Model 1 corresponds to the model used by Ahmad et al [7]. From Table 4 it is clear that the results vastly improve upon the previous reported results for gold farmer detection.

The best overall results are obtained from Model 6 which corresponds to the model which is constructed by combining the item based features with the item-network features. Model 3 also gives a relatively high value for recall but the value for precision and F-Score is much less that that of the combined model. Interestingly Model 7 which corresponds to the combined model and which uses features from all the previous models does not perform as well but it still performs better than the baseline model. Also noteworthy, is that Model 2 and Model 4 have similar F-Score but the trade off between precision and recall for each is observed.

Thus, for model selection, the main criteria that one has to address in this domain is not just the performance in terms of these metrics but also the human effort is required to determine if the person who is flagged is indeed a gold farmer or not. This is so because in some contexts there is a high cost associated with flagging gold farmers incorrectly. In such contexts a model with high precision is highly desired. In other contexts where gold farming related activities have a high volume and there are a high number of gold farmers within the game, recall is a more important metric. The choice between these two models will thus depend upon the requirements of the domain.

Table 4. Prediction Results from the various models used

Model	Precision	Recall	F-Score
Model 1	0.721	0.657	0.687
Model 2	0.747	**0.873**	0.805
Model 3	0.723	0.694	0.708
Model 4	0.866	0.749	0.803
Model 5	0.703	0.716	0.709
Model 6	**0.943**	0.729	**0.822**
Model 7	0.728	0.683	0.705

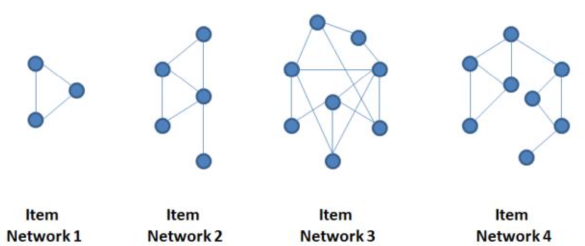

Figure. 9. Network of Items with more than half a million transactions

VI. Summary

Trade is an important aspect of gaming in MMOGs. Previous work on the economies of MMOGs has demonstrated that many real-world phenomena can be mapped onto virtual worlds [1]. Because of challenges related to data collection in the offline world, it is not possible to study certain types of phenomenon in sufficient detail, especially phenomenon related to the study of clandestine activities and their associated networks [3]. Thus, virtual worlds offer an opportunity to bridge this gap and study such phenomena in much more detail than is possible in the offline world. The insights gained from studying virtual worlds can be applied to the real world if sufficient mapping can be established between them.

One such problem that we addressed in this paper is that of trade associated with contraband and their item networks. After discovering a set of items which were most often associated with gold farmers, we used those items as well as the networks between them as feature sets in machine learning models to predict who the gold farmers are. The improvement of results demonstrated the viability of this approach.

VII. Conclusion and Future Work

The availability of datasets which contains information about clandestine activities opens new avenues of research for studying such activities. In this paper, we analyzed contraband trading activity and contraband networks in MMOGs. It was discovered that gold farmers sell certain items more than other players, and there are certain items they also buy more often. The items that gold farmers sell more often as compared to normal players are high end items that likely fetch more money. On the other hand, the items that the gold farmers are inclined to buy more often are the low end items. There are two possible explanations of why these patterns appear. One possibility is that they do so in order to corner the market and create an artificial monopoly over that resource. The alterative is that they do so in order to use them in crafting other items. In our future work we seek to address this issue.

Using insights gained from the analysis of contraband networks in MMOGs, we addressed the challenge of gold farming detection. While the difficulty of gold farmer detection has been addressed before [7], in this paper we extend the previous results by adding information from contraband networks as feature sets to enhance the prediction task. The approach that combined features from both the list of items and item-networks associated with gold farmers yielded the best results. In future work, we plan to expand the current analysis from contraband networks to a multi-network analysis which includes other networks in MMOs like the trust network [14], mentoring networks, chat networks and other trade networks.

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