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# Towards Analyzing Adversarial Behavior in Clandestine Networks

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**Abstract**

Adversarial behavioral has been observed in many different contexts. In this paper we address the problem of adversarial behavior in the context of clandestine networks. We use data from a massively multiplayer online role playing game to illustrate the behavioral and structural signatures of deviant players change over time as a response to "policing" activities of the game administrators. Preliminary results show that the behavior of the deviant players and their affiliates show co-evolutionary behavior and the timespan within the game can be divided into different epochs based on their behaviors. Feature sets derived from these results can be used for better predictive machine learning models for detecting deviants in clandestine networks.

## Introduction

Adversarial behavior has been observed in a large number of contexts and is almost ubiquitous in social settings. Mainly because of the difficulties associated with collecting data in such settings, adversarial behavior in criminal and clandestine networks has not been analyzed in detail. In this paper we address this deficiency by analyzing a clandestine network in a massively multiplayer online role playing game. The deviant behavior which is analyzed is called gold farming which refers to a set of related clandestine activities in online virtual worlds which are considered illegal activities within the context of the game (Lehdonvirta et al 2011). Trade of virtual items in online games using real money has grown significantly and this industry is now worth more than $3 billion dollars out of which 70 percent is accounted by gold farming according to a recent World Bank Report (Lehdonvirta et al 2011). Since gold farming is actually a set of related practices there are multiple types of behaviors that one can expect to be associated with gold farming.



## Adversarial Behavioral Networks in MMOGs

We use data from a massively multiplayer online role playing game called EverQuest II for studying this problem. The dataset spans nine months from January to June in 2006. We concentrate on the type and volume of activities performed by gold farmers vs. normal player. Consider the time series of gold farmer behavior over the course of a day. Since there are multiple types of gold farmers one would expect to see multiple types of behavioral signatures to be associated with these behaviors. We use a scale and translation invariant distance measure used by (Yang et al 2011) to determine the distance between the time series.

$$\boldsymbol{d(x,y) = min_{\alpha,q} \frac{\|x - \alpha y_{(q)}\|}{\|x\|}}$$

Where $x$ and $y$ are time series, $y(q)$ is the result of shifting time series y by $q$ time units, and $\|\cdot\|$ is the $L2$ norm. We use the KC Clustering algorithm (Yang et al 2011) to cluster the time series of the players.

Additionally we also plot the intensity of tradition activities of gold farmers and normal players over the course of the timespan in Figure 1. The top part of the figure shows the overall trade activity contrasted with the gold farming activity. Application of change detection algorithms reveal that the player and gold farmer behavior can be divided into three distinct epochs. The graph at the bottom shows the gold farmer trading activity further broken down into buying and selling activity for gold farmers. External information about the enforcement of official policies against gold farmers revealed that the end of the first two epochs corresponds to the enforcement of policies against gold famers.

At first it may appear that the number of gold farmers has decreased. This is however not the case as the percentage of new gold farmer account being created

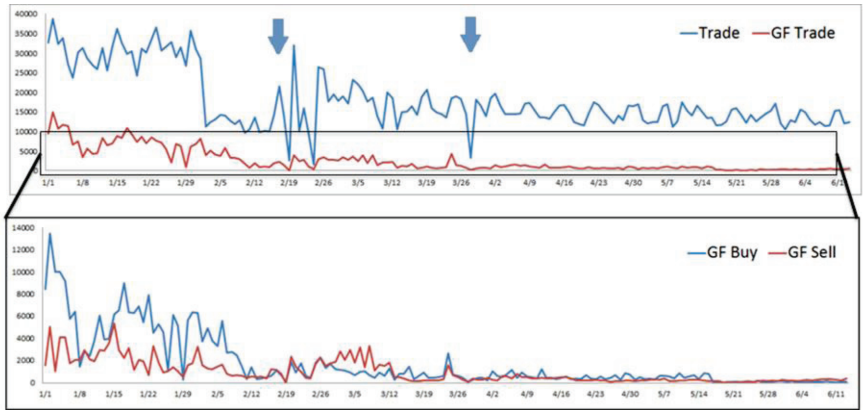

Figure 1: Intensity of trade activity over the course of 32 weeks

increases from less a percent to more than 10 percent in mid-April 2006 even though the trading activities of the gold farmers decreases. The most likely domain explanation for this change is that the gold farmers have changed their behaviors as a consequence of the enforcement of policies and are thus more difficult to catch. We note that earlier work on gold farming established that not all the gold farmers are identified as such in the dataset so that the trade volume is likely to be higher (Ahmad et al 2009). More interesting patterns however start to emerge if we consider how the behaviors of gold farmers change over time. If we cluster the time series data based on separately clustering the time series associated with each epoch then we get different types of dominant behaviors associated with gold farmers. Figure 2 shows the various types of gold farmers which are discovered over time via the clustering approach. It should be noted that the dataset does not distinguish between the various types of gold famers and these are discovered via the clustering approach. The literature however talks about the various types of gold farmers with different expected behavioral signatures. Gatherers refer to Gold Farmers which do most of the virtual item collecting work; Bankers save the virtual gold in their accounts and mules transport the virtual goods within the game (Ahmad et al 2009). Thus Figure 2 shows that the proportion of the various types of gold farmers changes dramatically over time. This is to be expected if the gold farmers are changing their behaviors because of external pressure. In conclusion we note that it is observed that gold farmers actively change their behaviors as a result of enforcement by the game admins and thus there is interplay between the change in the gold farmer behavior and the admin's behaviors. Our current and future work involves the discovery of frequent evolving graphs to analyze the co-evolution of this clandestine network with respect to specific policies enforced as well as admin's behavior.

## Related Work

A number of studies on Gold Farming have been done before. Machine learning techniques have been applied for

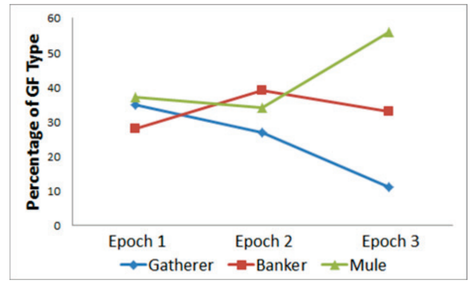

Figure 2: GF Types over time

automatic detection of Gold Farmers (Ahmad et al 2009) Comparison of trade networks of deviant players in MMOGs and drug trafficking networks revealed that these networks are very similar to one another as compared to other types of social networks (Keegan at al 2010). Analysis of their trust networks reveals that the gold farmers trust players who are trusted by many other players in order to conceal their signatures (Ahmad et al 2011).

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