The Contagion of Malicious Behaviors in Online Games

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ABSTRACT

This article investigates whether individual users are more likely to display malicious behavior after receiving social reinforcement from friends in their online social networks. We analyze the dynamics of game bot diffusion on the basis of real data supplied by a major massively multiplayer online role-playing game company. We find that the social reinforcement, measured by the ratio of bot friends over total friends, affects the likelihood of game bot adoption and the commitment in terms of usage time.

Categories and Subject Descriptors

J.4 [**Computer Applications**]: Social and Behavioral Sciences – *sociology*

General Terms

Management, Security

Keywords

social contagion, diffusion model, online game, game bot

1. INTRODUCTION

In massively multiplayer online role-playing games (MMOPRGs), players engage in a variety of interactions with other players and form online social networks. A complete digital record of players' activities in MMORPGs provides a promising opportunity to study the dynamics of human behavior. As online social networks have begun to play an important role in shaping behavior, the analysis of human interaction in the context of online friendships has become a viable research topic. Extreme opinions/behaviors were also explored in diffusion models [1]. The use of drugs, tobacco, and alcohol have been proven to have a significant effect on the contagion process between people. The popularity of online social networks has spurred researchers to study the diffusion of user behaviors. Centola [2] conducted an experiment to trace health behavior diffusion in online communities. Romero et al. [3] studied the adoption of the specific function in Twitter. MMORPGs are also an interesting arena to observe how behavior spreads, a subject has not yet been deeply explored. In this article, we aim to analyze the dynamics of bot diffusion based on real data of major MMORPGs and to test whether individual adoption is more likely when users receive reinforcement from multiple friends in their social networks. We focus on malicious behavior, especially the use of game bots that do cheating automatically without player's control. Understanding malicious behavior dynamics will enable us to build effective counterstrategies.

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2. RESULTS

We used the dataset (between December 21, 2010, and March 21, 2011) from AION, a prominent MMORPG developed by NCSoft. In Aion, like other MMORPGs, there are various networks depending on interaction types such as communication through chat, email, messaging, trade, party play, joining guilds, and building friendships [4]. Here, we specifically focus on friendship networks formed by individual normal users. We excluded the gold farming workshops because gold farmers do not form friendships with others, even members in the same group. Generally, only bankers and merchants who trade assets develop friendship networks. In Table 1, we present characteristics of the friendship networks of Aion and ArcheAge (until Jan-13). ArcheAge is a recently launched MMORPG developed by XLgames, and its social network is still in its initial stage before the appearance of the game bot. Compared to well-known social networks [5], Aion users have fewer friends and user's friends tend not to form extended networks.

Table 1. Summary of the basic network characteristics

	Nodes, #	Links, #	Avg. degree	Clustering coefficient
Aion	18,761	80,026	4.3	0.073
ArcheAge	11,433	33,724	3.0	0.076
Facebook	63,730	817,090	25.7	0.22
Flickr	2,302,924	22,838,276	20.9	0.18

In January 14, the adoption ratio, the ratio of characters newly marked by the bot detection code, namely new adopters, over total active characters was 0.04(963/19,833). Of 19,833 characters, 10,508 characters formed a friendship network and 128 characters were suspected to be new adopters. We consider the characters who did not have bot usage records during December 21, 2010 and January 13, 2011 as new adopters. On the network formed before January 13, the adoption ratio reached 10.91% and the increase of the adoption ratio became saturated after 40 days. This implies that the game company needs to restrain users from using bots from the beginning stage of the game to prevent contagion of friends. For the initial test of contagion, we calculated the bot adoption ratio, which was 0.16 when the user was exposed and 0.05 when the user was not exposed. We measured the social reinforcement effect on bot adoption in terms of various metrics:

- Accumulated signals from friends: bot_score

- The number of bot friends: influential_no
- The number of friends: related_no
- The largest signal from bot friends
- Number of banned friends for bot usage: anti_score
- influential_ratio=influential_no/related_no

Figure 1 shows the cumulative distribution functions (CDFs) of new adopters and normal users according to the degree of social reinforcement measured by each metric. The more friends a character had and the more friends who adopted game bots, the greater was the character's tendency to adopt a game bot. However, characters who received larger signals from friends and who accumulated more signals from bot friends did not increase the chance of game bot adaptation. The experimental findings were quantified as the hazard ratio. A discrete-time hazard model estimated the hazard ratio of influential_no, related_no, and influential_ratio at 1.041, 1.011, and 3.222, respectively, excluding anti_score. This implies that the ratio of bot friends over total friends has the largest influence on game bot adoption. Despite the expectations of game companies, banning individual users does not prevent the infection of game bot usage (i.e., players adopt game bots regardless of whether their friends are banned or not). At the individual level, results show that the high ratio of bot friends over total friends increases the likelihood of adoption (Figure 2). This implies that social reinforcement from many friends makes players much more likely to yield to the temptation of the game bot. However, when the ratio exceeds one-third, the likelihood decreases.

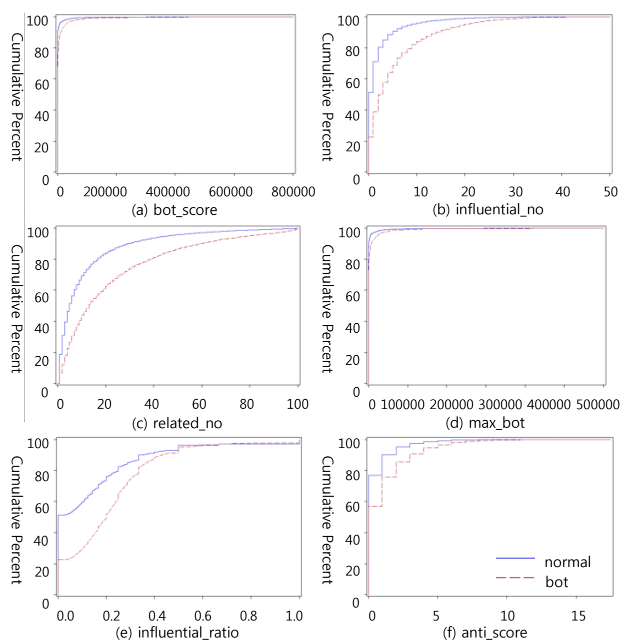

Figure 1. (a)~(f), CDFs of new adopters and non-adopters

The secondary issue is the level of commitment that users have after adoption. The influential ratio also affects how long the character uses the game bot but does not affect how frequently the character uses the game bot (Figure 3). Furthermore, we tested whether adopters keep or stop using the game bot according to whether he or she is exposed. The retention rate of the game bot was 0.61 when the user was exposed and 0.40 when the user was not.

In all experiments, we found strong evidence for the diffusion of malicious behavior on friendship networks in MMORPGs. Specifically, social reinforcement measured by the ratio of bot friends over total friends affects the likelihood of adoption and the commitment in terms of usage time. Our current work includes the analysis on the effect of network structure on the diffusion process. For that, we perform the community detection and trace the diffusion process according to the community. Second, we investigate the effect of social reinforcement on stopping malicious behavior. We expect the anti_score to have a positive effect on stopping bot usage and influential_ratio to have a negative effect.

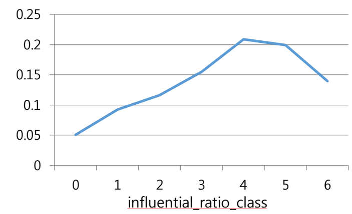

Figure 2. The bot adoption rate vs. influential_ratio

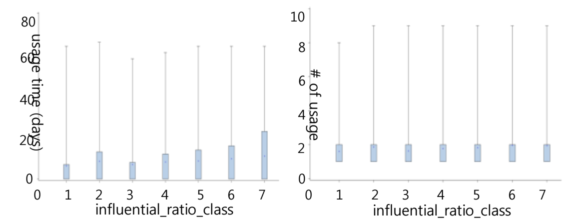

Figure 3. The level of commitment vs. influential_ratio

3. ACKNOWLEDGMENTS

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