AN ANALYSIS OF SOCIAL ACTIVITY INFLUENCES IN ONLINE VIRTUAL WORLDS

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ABSTRACT

Online game is a trendy application in social networks which gets more players' attractions nowadays than traditional PC game, which does not include social interactions. Existing study in social networks focused on discovering the influencers coupled with influence diffusion, this paper identifies the activity which may increase player's personal influence in the networks. In our research, an online virtual world named RooMi in Taiwan is applied to be investigated (1) whether a player increases his/her influence by hosting a public activity, and (2) the most important public activity that increases most influence by different kinds of players. This analysis result on influential activities in the virtual worlds can be a mirror to reflect the real world, which data is hard to be accessed and simulated.

Keywords: social networks; virtual worlds; influence increase

1. INTRODUCTION

As surfing in the social networks is becoming one of modern people's daily activities, virtual worlds or MMORPG (Massively multiplayer online role-playing game) connecting with social networks consequently get more public's attention. Those adults who did not play games step into the virtual worlds as gift giving interactions increased between friends in the social networks. The volume of registered active accounts in the virtual worlds has reached 1,899 million in 2012.

Selling virtual goods or real money is an increasingly popular revenue model for MMOs and virtual worlds. Virtual goods can range from weapons in online games to clothes and decorations in virtual worlds. The items are used as part of game play or to fulfill social and aesthetic functions[7]. Due to microtransactions and no delivery cost, players tend to buy virtual goods to enjoy the immediate hedonic value of virtual goods. The virtual world platforms also easily gain direct revenue from selling virtual goods. The paying users have reached 97 million in 2012[10] and the worldwide market for virtual goods to reach $14.8 billion in end of 2012 [13].

As the virtual worlds market is booming, finding an efficient way to sell goods is becoming a spotlight. There has been some study discussing influence in online social networks via viral marketing. As for system providers, it is an efficient way to market those influential users to gain best benefit with lowest cost. As for players, when users may influence others' shopping decision, s/he feels being required in the society. The belongingness feeling increases their stability in the virtual worlds[3]. Social presence is one of the reasons why users stay in the VW. Therefore, it is important for virtual-world players to know how to efficiently increase personal influence under the norms. In the other hand, for virtual-world platform, more user interaction means more stay time and sales. So the platform can enhance those effective social activities to generate more revenue.

Even though the market of virtual worlds has gained attention, there is little research focus on virtual worlds influence. A virtual world is an electronic environment that visually mimics complex physical world. Animesh states the 3D representation of space in virtual worlds brings them closer to the physical world and it helps the researchers refer the existing research results in physical world. However, there are some reasons that make it difficult to refer related study. First of all, it is difficult to obtain large scale social networks data and evaluate the influence of the social networks in the real worlds. Secondly, in the electronic social networks, such as Facebook, it is difficult to map the real attendance and the attendance announced in the activities. There is also no mechanism to assess user's influence difference after hosting activities. Thirdly, in the domain of blogs, even some bloggers host activities to enhance their fame by directly communicate with surfers, such as face-to-face classes and book signing, those activities invitations are hidden in the sea of blogs and the real attendance are unrecorded.

Most of existing study focused on the influencers coupled with influence diffusion, this paper focuses on analyzing features of social behaviors or activities that can effectively increase user influence.

This paper has the following three contributions,

1. Our research proposed an influence evaluation methodology and measurement for social networks in the virtual world, in which has heterogeneous contacts for all users.

2. In the presented model, we demonstrate that the influence may be affected by different kinds of social activities for different kinds of users in the virtual worlds.

3. It is difficult to acquire social networks data in the real world. Simulating the experiment in the virtual world maybe a good solution to help us understand how people enhance personal influence in the real world.

In the following sections, we first introduce related work in social computing, and then elaborate the methodology and study approach we propose. In the experiment stage, we applied data in the RooMi platform to analysis the social activities. Section 5 closes with some conclusions and observations.

2. RELATED WORK

2.1 Social Influence

With the rapid increase in popularity of online social community, a number of empirical papers of social influence analysis have attracted research interests and have been studied for a decade; and majority of the works present qualitative findings about social influence [11, 15] with the formulation of the problem of topic-level influence mining. And in[6], the probabilistic model was applied to verify if the behavior of users is influenced by their neighbors, and demonstrated that social influence has stronger predictability to the user behavior than correlational influence. In order to identify the influencers in the community, some quantitative methods are proposed to measure the influence score and to find the influential users. For instance, in investigating blogosphere [1] [2] [12], a platform that user can express personal experience and knowledge on an event or a product, it's necessary to take the behavior of blogging (i.e., posting, reading, commenting, and scrapping) into consideration for clearly recognizing who the productive and influential bloggers are; and a latest study [2] reports that temporal information does matter due to the significant temporal patterns in the blogging behavior.

2.2 Influence Propagation

For understanding the phenomenon of information propagation through a social network in the field of social science, such as Gruhl [5] and Tang et al. [14] who tried to investigate the influence of social network were both interested in identifying the set of postings which have relevance to some specific topic and discovered the diffusion of various topics in blogospheres effectively. Despite of the studies of influence spreading, for allowing information and ideas to spread in the large-scale online social network sites in a short time with limited marketing budget; Kempe et al. [8] [9] proposed a greedy approximation algorithm which guarantees the influence spreading within (1-1/e) of the optimal influence spread to mathematically maximize the spread of influence, and proved that the optimization problem is NP-hard. Additionally, a new heuristic method proposed by Wang and Yang [4] is subjected to solve the efficacy problem. However, instead of trying to discover the features which affect the increase of influence, most works focused on validating the existence of influence. Moreover, there are few studies explored online social game platform as it becomes more and more popular. In the present work, we collect the data in a real-life online social game named RooMi that makes our experiment ground truth. And we not only explore the behavior of players, but try to find which actions or behavior are the key factors for influence increasing to the different characteristic of players.

3. STUDY APPROACH

3.1 Research Framework

This study aims to reveal the affective activity in the social networks of virtual worlds. The research framework is depicted as Figure 1. The methodology is followed by three phases. The first phase is to determine influence measurement index; the second phase is to classify users into different influence levels for detecting effective activities; in the third phase is to analysis the user activities of different levels.

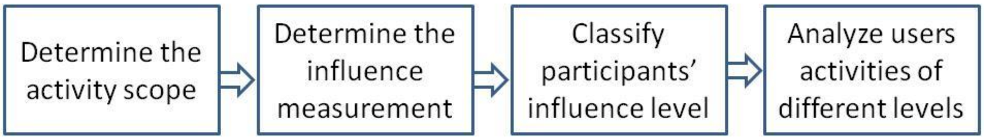

Figure 1 Research framework

3.1.1. Determine activity scope for experiment

There are thousands of activities in the virtual worlds. Players may do personal activities like role-play, house decoration, writing diary; s/he may perform user-to- user interactions like gift giving, visiting, writing mail; and s/he may host public activities those published for the public users like voting, beauty elections and auctions. In this study, the activity scope for the experiment is specified in the public activities that hosts announced in the central bulletin board.

3.1.2. Determine the influence measurement

There are several ways to measure the influence value of players, such as number of friends, number of visitors, or number of followers. 'Visit' is an activity that user *u* goes to user *v's* home. A user's visit count is how many times others went his/her home. In this study, we evaluate whether visit count is an effective measurement to evaluate a user's influence difference after hosting activities.

While user *u* visits user *v*, it implies that *u* is curious about *v* and wants to understand *v*, just like fans (user *u*) to a superstar (user *v*). In this circumstance, user *v* has directed influence to user *u*. The test of significant was performed to verify that whether user's influence was enhanced after s/he launches an activity.

3.1.3. Classify participants' influence level and define the scope of activity

Every user's influence is regarded as his/her visit count. In this phase, users were separated into three levels: high influence, middle influence, and low influence. The users in the top 25% visit count is in high influence level; the 25%~75% visit count users were grouped into middle level and the last 25% were in the low influence level.

3.1.4. Analyze users' activities in different influence level

In this step, we identify the important activities that attract huge attention in different influence levels. For example, players who have high-level influence might enhance their influence by host social party; on the contrary, players of low-level influence usually promote their influence by beauty elections.

3.2 Dataset

RooMi (http://www.roomi.com.tw) is an online virtual platform for users to make friends, do leisure activities, and play games with their friends. It provides numerous social games as other social networks; on the contrary, RooMi integrates different social games in a virtual city as shown in Figure 2 (a) and gives players level record which is social networks platforms do not have. Users can gain the latest situation about their friends effectively, decorate their house, dress up their avatar, and interact with other players in the game, as shown in Figure 2(b), (d). The game and scene will change with several festivals. As Valentine's Day approaches, the virtual worlds provide greeting card service, game and gift giving as shown in Figure 2 (c). The virtual world providers may gain profit from those virtual chocolate gifts, sweetheart icons or teddy bears bought from players. The variety of choices is a major characteristic that draws users in the virtual worlds. The variety of choices also attracts different users to the divergent aspects of games.

(a) RooMi Virtual World

(b) Dressing up the avatar

(c) Virtual house

(d) Interactive game: table tennis

Figure 2 Game scenes in RooMi (a) the virtual world has kinds of stores, such as convenient store, movie theaters, game center, parties and clubs. (b) Players may dress up their avatar with the costumes and accessories that bought from shops or exchanged from others. (c) Players may buy furniture and ornaments to decorate their house to show their taste. (d) Players may play against the AI or invite friends to join an exciting multi-player battle, such as table tennis or fighting monsters.

3.3 Data description

The time period of retrieved data is from 2012/01/01 to 2012/06/30. The experiment scope was controlled within the activities that were announced in the central bulletin board by hosts. It includes 7 types of activities: vote, friend match, auction, bidding, beauty election, lucky draw, and others. Table 1 describes how 7 kinds of activities are performed in the Roomi. There were 792 activities held during this period. After removing 9 activities without any participants, there are totally 783 effective activities and 232,981 visit count. Table 2 describes attributes of players' profiles in RooMi.

Table 1 7 kinds of activities in the Roomi

Activity	Description
Vote	The player issues a topic and requests participants to vote in his/her home.
Social party	The player hosts a gathering party to invites participants to chat in his/her home.
Auction	The player announces to sell his/her stuffs in his/her home during a certain interval.
Bidding	The players who sell his/her stuffs in a fair.
Beauty election	The host decorates his/her home as a runway. Candidates may present themselves with their exquisites and being voted.
Lucky draw	The host bought a lottery box from Roomi and put stuffs into the box as prizes. All the participants may pay certain money to have one draw and take the thing he drew.
Others	It includes miscellaneous activities, such as players announce to sell stuffs in a specific price.

Table 2 Description of personal profile features in Roomi

Feature	Description
Gender	The gender attribute was filled by the player to generate his/her avatar's basic appearance.
Level	Statistical measurement of character development in the game. The information is used to differentiate beginners and advanced players. This measurement urges players to continuously enhance themselves to expert.
Registration-time	The feature states the time the player registered in RooMi.
Environment	Players can choose the house they prefer to live in with different rent; luxury house has higher rent.
Money	The expenditure the player spend on products, rent
Contribution	Number of contribution degree made by the specific player in the family.
Discuss	Number of the posts of the player in the forum.

4. EXPERIMENT RESULT

The first stage of the experiment is to verify whether visit count was significantly increased after participants launch activities. The significant level set to be α =0.01, and the hypotheses for this one-sided test is as follows,

H_0: there is no difference before and after user hosting an activity

H_a: user influence is positively associated with hosting an activity

Table 3 depicts the activity count and visit count for different kinds of activities. The total visit count 30-day before and after the activity launched are 614,777 and 795,238 respectively. The average and standard deviation of total visit count before the activity launch are 785 and 176. The *p*-value is calculated to be 0.0082, which is less than significant level 0.01 and ** $p < .01$. The result of the observation rejects H_0 and shows significant influence difference before and after activities. Figure 3 also demonstrates the significant difference in every kind of activities; therefore, visit count can be set as influence difference measurement for activities.

Table 3 Aggregate comparison of visit counts before and after activities host

	Vote	**Social party**	**Auction**	**Bidding**	**Beauty election**	**Lucky draw**	**Others**	**Total**
Activity count	41	16	252	16	17	342	99	783
Visit count -30 days	30,939	13,599	222,815	19,316	12,950	224,598	90,560	614,777
Visit count 30 days	41,007	16,686	263,232	30,303	13,774	310,864	119,369	795,238
Avg visit count -30 days	755	850	884	1,207	762	657	915	785
Avg visit count 30 days	1,000	1,043	1,045	1,894	810	909	1,206	1,016

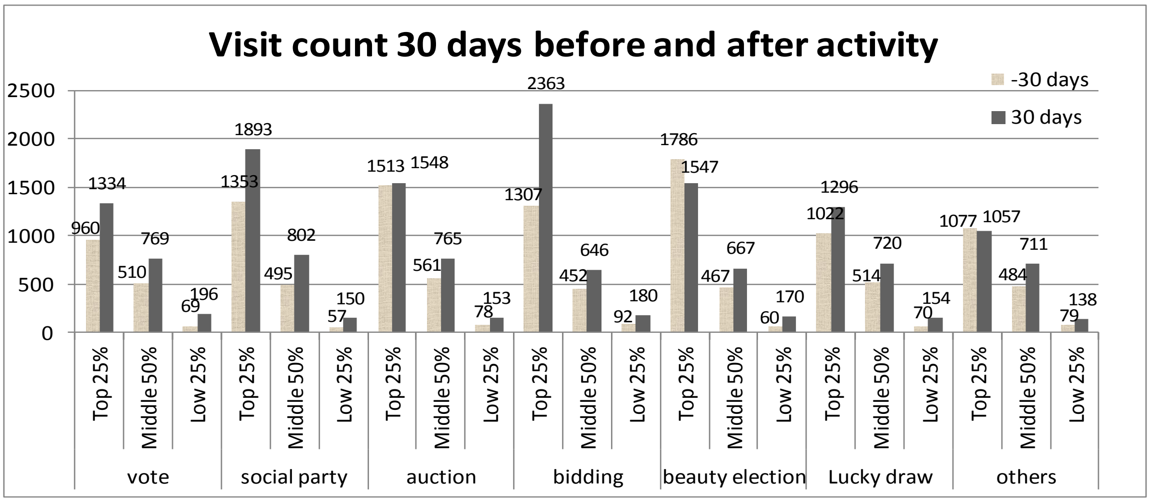

Figure 3 Comparing visit count before and after activity launched by different influence level

Table 4 and Figure 4 depict public activities host by different levels of players. The distribution of activity percentage seems similar in different influence levels. What worth a notice is that lucky draw stands almost half percentage activities in the lower level. This could be because lucky draw is the easiest activity to directly make virtual money. However, as shown in Figure 3, Comparing to bidding or social party, lucky draw is not a good method to increase social influence. Vote, social party and beauty election cannot generate direct revenue, but can attract attention.

Table 4 Activity host by different influence levels

Activity count	Vote	Social party	Auction	Bidding	Beauty election	Lucky draw	Others	Total
Aggregation	41	16	252	16	17	342	99	783
Top 25%	10	3	73	7	2	75	26	196
Middle 50%	22	5	117	7	10	172	58	391
Lower 25%	9	8	62	2	5	95	15	196

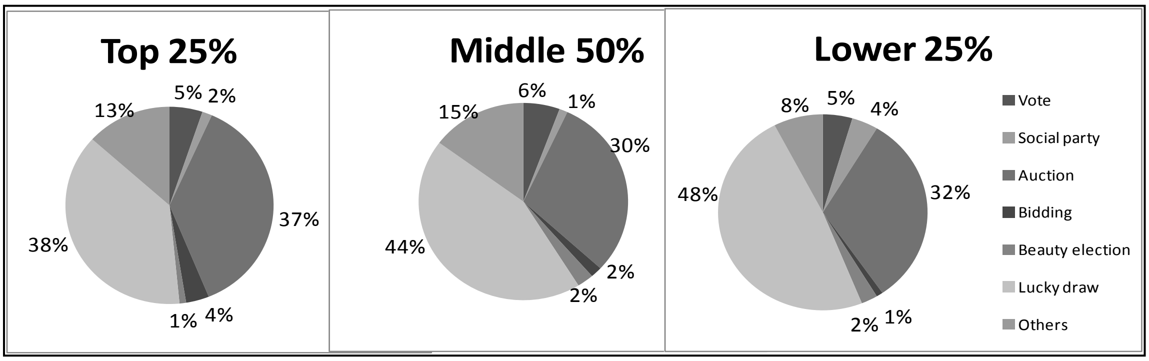

Figure 4 Percentage of activity host by different influence levels

Table 5 shows the average daily visit count in 3 days, 7 days, 30 days and comparing to 30-day before for the 7 activity categories. Every activity category has most visit count in the first 3-day and lowest average visit count in 30-day. It means that the influence of every activity will decrease as time goes by. However, comparing 30-day before and after the activities, host activities still enhances players influence in the long term.

Table 5 daily visit count 3-day, 7-day, 30-day after and 30-day before activities host

	Vote	Social party	Auction	Bidding	Beauty election	Lucky draw	Others	Total
-30 days	25.8	28.3	29.6	42.9	25.4	22.1	30.8	26.4
3 days	98.0	85.7	100.1	149.1	71.6	91.4	96.4	95.8
7 days	67.2	66.5	67.1	94.0	49.1	59.1	69.7	64.1
30 days	33.3	34.8	34.8	63.1	27.0	30.3	40.2	33.9

Figure 5 shows the average visit count 3-day after activities launched for different influence levels. Compared to middle and low level users, the top 25% users always have more visit count after every kind of activities. In the short term, the most influential activity in the high influence level is hosting social party, which shows significant increase among all the activity categories. Although vote activities and other miscellaneous activities gain the highest visit count in the middle and lower levels; however, they do not show notable influence difference than other categories. Compared with Figure 3, social party and vote increase most influence in the high and middle levels for the long term, which is consistent with the short term activity effect.

Figure 5 Average visit count 3-day after activity launched

The reason why social party enhances more influence in the short term could be because the host must decorate his/her house with his/her exquisite furniture to attract players to participate in the party. Therefore, even the social party is over, players keep on visiting the decorated house and borrow the idea to decorate his/her own house. Bidding is not the top influential activity in the short term as shown in Figure 5, but becomes the top in the long term comparing Table 3. While a buyer strolls along the fair, s/he is finding something among variety of sellers s/he may be interested or without purpose. When players find sellers have the same style with him/her, s/he will keep on visiting the seller and build long term relationship. Therefore, selling stuffs in the fair can be a method to build long term influence.

5. DISCUSSION

Social network services are prevailing and influence mining has been studied in the last decade. This paper introduces a novel research model to analysis the activity influence of social networks by combining a virtual world platform. The platform put people who are interested in making friends, interaction with public and playing games together, and makes them more intensive than traditional social media. In this paper we verify that visit count can be an affective measurement in virtual world's social networks. It also provides the analysis of the activities in different influence levels.

In this study, we mainly considered public social activities in different influence level; however, the way players enhance the influence in the games might have diverse results due to different game cultures and characteristics. Secondly, the influence of players in the game is evaluated by visiting relations, which might not guarantee that a player is exactly affected by the other player; on the other hand, further observations of the social relationships between users is required.

6. Acknowledgment

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