

Diffusion dynamics of games on online social networks

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Abstract

Social games, being embedded in and drawing upon existing social networks, have the potential to spread virally. In this paper, we examine two popular social games, each having millions of Facebook users, to understand the role that users play individually and collectively in propagating social applications. At the individual level, the users' invitation behavior significantly outweighs their demographic and social network properties in predicting invitation success rate. At the collective level, we demonstrate that social games that encourage group formation tend to rapidly assimilate dense network cliques. Finally, engagement in a social game is closely tied with the ability to recruit friends.

1. Introduction

Games are a ubiquitous form of social interaction. Not only do they help sustain friendships, but they are more fun when engaged in with friends. It is little wonder that online social networking platforms are a fertile substrate for the development and propagation of social games. Since Facebook, one of the most popular social networking sites, opened its platform[9] to developers building third party applications, there has been an explosion of social games¹, both in number and popularity. Current social games are often “turn-based”²: the gaming experience is built up by social interaction and inter-dependency. For example, one of the most popular social games on Facebook (FB), FarmVille has gained over 80 million monthly users in less than one year.³ Users interact by growing crops, helping neighboring farms and exchanging gifts.

In contrast to traditional collaborative online games such as World of Warcraft, where users form social ties anew, social games are embedded in and interact with users' existing online social networks. Today's social games, being simple and lightweight, are amenable to small-scaled and rapid development. They can also quickly reach a large user population. For example, one

of the games we investigate in this work, Diva Life, took just four weeks from its launch date to garner more than a million users. An important driver of such rapid growth is the ability of players to invite their Facebook friends to the game. In this paper we examine the role that such social referral mechanisms play in the rapid propagation process, and its consequences for online social interaction and viral marketing.

In particular, we relate users' individual invitation behavior to the yield for those invitations. In addition, we analyze the collective influence of neighbors in the social network and in invitation cascades. As the first empirical study on the social influence and diffusion in social games, we believe this work can shed light onto how social game diffusion processes are connected to, shaped by, and co-evolve with other types of interactions in the social networking space.

This paper is organized as follows: after discussing related work on diffusion, we provide some background on the Facebook platform and social games and introduce the particular game instances we studied. Our analysis is composed of two parts: predicting invitation efficiency and understanding the group and social dynamics of invitation networks. We conclude with a discussion of our findings and future work.

¹ <http://www.insidesocialgames.com/about/>

² <http://www.socialtimes.com/2008/07/social-games/>

³ <http://www.facebook.com/search/?q=farmville&init=quick#!/FarmVille>

2. Related Work

There is a rich literature on diffusion of cultural fads [5], innovation [17], or products [13]. In his book “Diffusion of Innovations,” Rogers discusses the five stages of an individual adoption process from a microperspective, but also the macro-perspective on change in diffusion rate over the course of the diffusion process. By viewing the diffusion process as the transmission of items between individuals, various contagion models have been adapted from mathematical epidemiology [2]. The Bass model[4], used to describe the diffusion of innovations, is an example of an independent interaction model, where each exposure independently can result in adoption. In contrast, in threshold models the adoption probability depends on the number of simultaneous exposures[10, 16]. A model proposed by Dodds and Watts generalizes from the above two types of contagion models by explicitly incorporating memory of past exposure to an infectious agent [7].

In addition to modeling the statistical properties of diffusion, social perspectives and implications have also been explored. For example, Bikhchandani et al. studied individuals’ tendency to learn from and imitate others and explained the role of this behavior in diffusion of cultural fads [5]. On a macro-level, for example, critical mass theory [15] describes the relationship between the growth of adoptions and network externality [9]. On a micro-level, studies have modeled adoption and coordination processes with various influencing factors including network structure [6, 11, 12]. Further work has attempted to model individual customer’s “network value” in terms of the expected profit from others that customer influences [8].

The rich traces users leave in the form of social networks and interactions online have started to enable researchers to conduct large-scale studies of diffusion patterns. Leskovec et al. observed a power-law distribution of online recommendation cascades and proposed a model to identify community structure, product features, and pricing strategies for successful virtual marketing [13]. Liben-Nowell and Kleinberg found and modeled surprisingly deep cascades of online chain email [14]. Even the act of joining a group can be considered a diffusion process. Backstrom et al. found that whether one will join a group depends not only on how many friends one has in the group, but also how these friends are connected to one another [1]. This is an illustration of network externality, since both the scale and structure of the converted network matters in exerting utility. A similar trend was seen in the adoption of gestures in the virtual world Second Life, where rates tend to quicken when more friends have adopted [3].

Finally, most relevant to our current study, Sun et al. analyzed the contagion processes of Facebook *Fan pages* and found that diffusion chains usually start from a substantial number of roots and users’ demographic or usage information are poor predictors of how widely an item will diffuse [18].

In contrast to the diffusion of fan-pages, which may require little interaction past the event of joining, our current study focuses on the diffusion of games. Despite the great popularity and business potential of on-line social games, there are relatively few studies that directly investigate social applications built on various social networking platforms. Gjoka et al. (2008) used data reported by FB on application installations of 300,000 FB users to identify general statistical patterns. These patterns include skewed adoption rate across applications, an increase in the total number of applications installed, a decrease in average usage, and a tendency of users to add to their already growing collections of apps. However, these aggregate observations tell us little about how individual applications diffuse as a result of local interactions.

3. Description of games and data

Our study focuses on two social Facebook games, using data provided by Lolapps, the company that created both games. Users’ information has been de-identified prior to analysis. Lolapps is a social gaming company founded in 2008, that has over 200 million FB users across all its games and applications. We focus on two of the Lolapps games that have enjoyed wide popularity: Yakuza Lords (YL) and Diva Life (DL).



Figure 1 Screenshot of Yakuza Lords in Facebook

Yakuza Lords (YL). Launched in July 2009, YL is a Role-Playing Game (RPG) with a mafia-theme in the context of Japanese culture. Players choose roles as Japanese mobsters and complete tasks, purchase items and manage property aiming at becoming the next “Yakuza lord”.

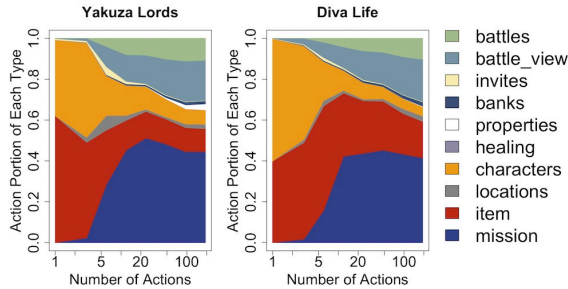


Figure 2 Action types as users gain experience in YL/DL
 –Best viewed in color

Diva Life (DL). DL was launched in Sep 2009. Like YL, it is an RPG and contains similar elements to YL but with a different theme, focusing on the fashion and entertainment business, with players dressing up and doing "gigs" to gain money and publicity.

User demographics: As of February 2010, YL had reached one million active users, with over 85% being male. Although launched 2 months later than YL, DL gained over 2 million monthly active users in the same period. As a game targeted at women, DL has more than 96% female users. The age distributions are similar and range from teens to 70s, with the majority being in the 18 to 38 years old range.

Families, invitations and the social network: As shown in Figure 2, typical actions for players in YL or DL include accomplishing game missions, purchasing virtual items, engaging in battles against other players or inviting friends on Facebook to join their families. A “family” or an “entourage”, as it is called in DL, is a social group inside the game and a player can be part of multiple families. The size of one’s family plays a role in how well the player does in the game, mostly influencing the outcome of battles and other kinds of competitions with other players. Therefore, family memberships enhance game play and possibly the social experience of the game as well.

In order to grow their families, players bring part of their FB social network into the game by sending invitations via FB. When a user accepts an invitation, he becomes a member of the inviter’s family. If the invitee has not already downloaded the game, they are presented an opportunity to do so in the invitation.

The dataset includes actions such as the issuing and acceptance of invitations, but also a detailed participation history in the game including completing tasks and purchasing virtual money. This data is complemented by user profiles: public information on the players including general demographics and friend lists. Users must explicitly allow such information to be shared and

different users share different portions of their profiles. For example, from our data, around 90% of users share their locale information, 40% of users share their friend list but only 1% share their relationship status. Making do with the data we have, we use invitations as partial projections of the social graph. When estimating properties relating to e.g. the size of a user’s FB network, we use data only for those users who have shared such data.

3.1. Marketing: Drawing upon Social Networks

Social games exist on top of social networking platforms and thus users’ social networks are utilized extensively in game marketing and in-game activities. In particular, social games enable players to easily invite their friends to join them in the game. This explicit and directed recruitment method is complemented by passively influencing one’s friends by posting to one’s news feed. Friends receive updates of the user’s activity in the game, and may be introduced to the game by clicking through the news feed item (See Figure 3).

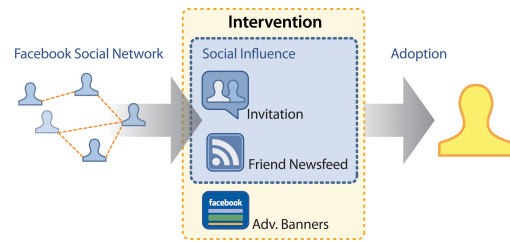


Figure 3 Referrer network in social game adoption

Although we cannot differentiate how much one adopter has been influenced by invitations, news feeds, or offline recommendations, a substantial number of adoptions do occur following an invitation. For example, out of all players who downloaded the two games analyzed here, more than 37% (for YL) and 25% (for DL) received invitations from their friends before starting to play the game.

Even though invitations are not the main channel by which users land in a game, we find that the users’ engagement in the game is substantially higher for those who join through an invitation. Figure 4 shows that compared to players who have never been invited, invited users remain in the game longer. Around 80% of non-invited players leave the game within the first day and almost none keep playing longer than 80 days. But among invited players, over 50% kept on playing for more than a day and 20% of all invited users were still playing 80 days later. This implies several possibilities. One is that social referral might more efficiently be targeting users who would be interested in the game.

Another is that invitations serve a recommendation role and cause a user receiving an invite to put a higher initial value on the application. Yet another is that the referral process can help establish scaffolding for social interaction within the game, thus improving the users' initial experience. We will address this further in section 5.

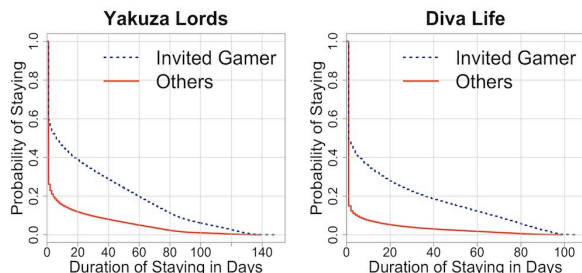


Figure 4 Users who received invitations to join a game stay active in that game longer.

Since the social referral mechanism is a major feature of social applications and has demonstrated significant importance in their marketing strategy, we concentrate on discovering the factors involved in these social interactions and the dynamics of the invitation network.

3.2. Game diffusion

Invitation behavior: Consistent with prior studies of online viral marketing [13], the number of invitations sent per user is highly skewed: firstly, only a few users invited a significant portion of their FB friends, shown in Figure 5a; secondly, while each inviter has invited 26 friends on average, the median number is 10. From the linear relationship between the average number of invitations sent as a function of the number of friends that users have, shown in Figure 5b, we interpret invitation behavior as being fairly casual. If that was not the case, we would see just a few close friends receiving invitations regardless of the total number of friends a user has. We suspect that many people simply send invites through the function of “invite your online friends” rather than carefully selecting invitees from among all their friends.

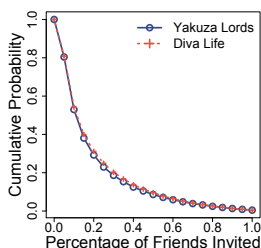


Figure 5a

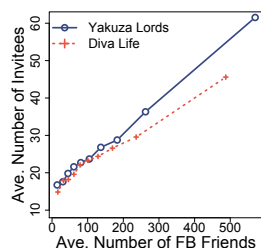


Figure 5b

Figure 5 a. Distribution of the fraction of their FB friends users invited over the course of game play; b. Average number of invitees as a function of the size of a user's FB social network.

Figure 6, depicting a portion of a diffusion cascade in YL, gives us a glimpse into how such a game diffuses over the social network. The cascade starts from a single user, and includes all the users who joined after being invited by the first user, followed by all the users who joined after being invited by those users, and so on. Note that all leaf nodes (users who joined but did not successfully invite any others) have been removed for clarity because the invitation graph branches widely in just a few steps. We also note that one user can be invited by multiple “ancestor” nodes and will discuss this further in Section 5.1.

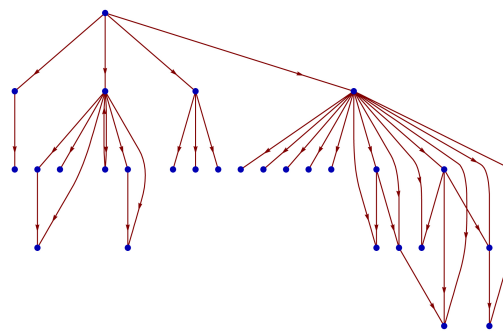


Figure 6 Sample invitation graph on YL

Figure 7 plots the average cascade widths at each level for 2000 randomly sampled diffusion cascades. Note that although each cascade has a distinct root node, these cascades are not separate, as they often run into each other when users from two different cascades successfully invite the same individual. The cascade width at each level represents the number of people who accepted an invitation whose minimal distance to the root node is equal to the level number. For both games, there is a quick expansion in the first 6 generations of invitations. Thereafter, the number of nodes at each level shrinks gradually until the maximum observed cascade depth of 28. This is evidence that social games are able to quickly explore the social network within a few steps and acquire potential users.

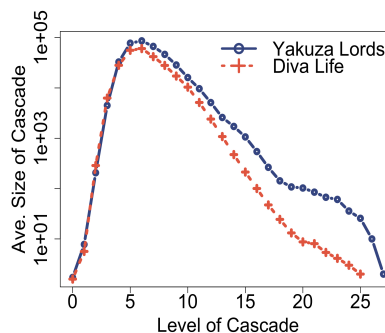


Figure 7 Size of invitation cascades by depth.

4. Invitation Network and Efficiency

4.1. Local Referral & Efficiency Models

One can be influenced to adopt FB games through a variety of channels, from direct invitations from friends to paid advertisements. In this paper we are interested specifically in the efficiency of game adoption of the social referral mechanism through the FB network, although we will consider the difference in behavior between users who adopt through referrals and those who adopt through other channels.

We characterize invitation efficiency from two points of view: the inviter, shown in Figure 8a) and the invitee, shown in Figure 8b). An inviter can invite multiple friends to the game. In this study we do not differentiate whether the invitees were already playing the game and were invited to join a different family, or whether they needed to freshly install the game.

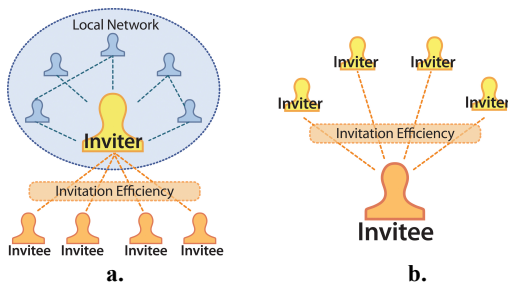


Figure 8 Modeling invitation networks. a) For each inviter, the invitation efficiency is measured over multiple invitees; b) for each invitee, invitation efficiency is exerted by multiple inviters.

In addition, from the inviter viewpoint, there are a variety of factors that could contribute to the overall likelihood that an invite is accepted, such as whether the inviter exerts more influence over her invitees, and what strategies she used in sending invitations. Thus we look at the invitation efficiency through these two components: who the inviters are and what invitation strategies they employ.

4.2. Invitation Strategies

Some users play a disproportionately large role in propagating games. Just 10% of users account for 50% of successful invites. We first examine their behavior in recruiting others to play with them. We identify four dimensions in invitation strategy and quantify how each affects the invitation *success_rate*. The *success_rate* is defined as the proportion of invited friends who have accepted invitations and is a way of measuring the inviter's efficiency.

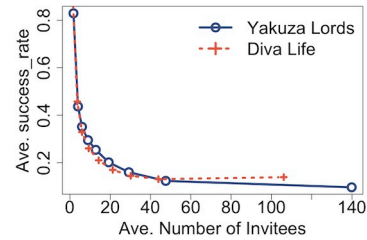


Figure 9 Sending more invites corresponds to lower per-invite success rates.

Volume We find that there is a strong negative correlation between the number of friends invited and one's invite *success_rate* in each game ($\rho > -0.77^{***}$), as shown in Figure 9. Clearly, *success_rate* decreases as more invites are being sent, most likely due to an indiscriminate invitation pattern. If there are only a limited number of friends interested in specific games, sending invites to many friends must then yield a lower *success_rate*. Since we are interested in additional factors beyond the number of invitees in one's ability to recruit additional players, we control for the number of invitees in our subsequent regressions. Based on the distribution of the number of invitees an inviter had, we choose three groups of inviters: those who have invited 6, 12, or 20 friends for each game in our dataset.

Pacing: Users can pace themselves differently in sending invitations; some will send many invitations in a short period of time, while others may take long pauses between invites. We interpret shorter time intervals between dispatching invites as a user having a lower discrimination threshold for contacting others. First we exclude users who sent no invitations or only sent them at a single point in time. For the remaining users, the median interval between sending invites is 3 days and the mean is 6 days. This indicates a long tail in the interval distribution, so we log-transform this variable. For our users grouped by number of invitees, we find a positive correlation to *success_rate* ($\rho = 0.09\sim 0.19^{***}$, in the 3 groups in which we controlled for the number of invitees per user). This implies that invitations that are more spread out in time are more likely to succeed (and possibly less likely to be perceived as spam).

Repetition: A user can invite the same friend repeatedly, demonstrating their enthusiasm and persistence in recruiting the particular friend. For the friend being recruited these repeat invitations mean greater intensity of exposure. As expected, sending more invites per invitee correlates positively with the *success_rate* of the inviter ($\rho = 0.23\sim 0.27^{***}$).

Selectivity: Users can invite their friends individually or be less selective by sending multiple invitations si-

multaneously with a single click. Controlling for the total number of friends a user has ever invited, the average number of invitations sent per click appears to be a significant factor for invitation *success_rate* ($\rho = -0.35 \sim -0.49^{***}$). That is, users who invite friends individually tend to have a higher yield, possibly because they target their invitations to those who are more likely to accept.

A linear regression that contains these three factors to predict the *success_rate* of inviters for each game shows all factors are significant and together account for more than 16% of the total variance.

4.3. Characterizing successful inviters

The next question ignores strategies employed by influential inviters, and rather addresses whether it is possible to identify them purely based on their profiles and activities other than the sending of invitations. We categorize inviters' attributes into three sets: demographic profiles, ego-network signatures, and relevant participation patterns in games and on Facebook.

Demographic profiles: Users' FB online profiles provide some public demographic information: gender, education, hometown, and relationship status. This rich data fails, however, to identify influential inviters, who are distributed randomly across various demographics, with the exception of age: we observe that being older does confer a bit more authority and influence - $\rho(\text{success_rate}, \text{age})$ falls into $0.06 \sim 0.1^{**}$ when segmented into groups by number of invitees for both games.

Ego-network structure: Beyond demographics, users can also be differentiated by the structure of their FB connections. We can consider how many friends they have, whether those friends are connected to one another, and how similar those friends' profiles are using a Tanimoto coefficient[19]. We limited our analysis to just those users with complete ego-network structure, that is those who share their FB friends list publicly.

In general, we find that popular users (those having many friends) tend to send more invitations (see Figure 5) and hence successfully invite more people to a game. However, the more users an inviter tries to recruit, the smaller is the *success_rate*, as shown in Figure 9. Having more friends on Facebook tends to yield very slightly lower *success_rate* on average ($\rho(\text{success_rate}, \text{number FB friends}) = -0.04^{***}$ for DL yet not significant for YL). Although this may at first seem counter-intuitive, it is likely that a larger ego-network includes many weak ties over which it is more difficult to exert influence. In addition, the tightness of one's social cir-

cle, measured in terms of the clustering coefficient of the inviter's ego-network had no bearing on invitation *success_rate*.

It is puzzling that the size and density of one's FB network has little predictive power. A possible explanation is that these networks can be largely static and do not reflect the level of interaction between friends.

Participation patterns: On the other hand, we find that variables relating to interaction on FB can be related to users' ability to influence others to adopt in both games. The number of posts on one's wall is a very weak but statistically significant predictor of influential inviters ($\rho \sim 0.04^{**}$). Wall posts reflect the users' own status updates, messages from their friends, and updates generated by apps, including games. Interestingly, we find the level to which one is willing to expose profile information publicly to also be very slightly correlated with *success_rate* ($\rho \sim 0.06^{***}$). These two measures serve as proxies for openness and engagement in online social networks, and thus suggest a relationship between social influence and social activity.

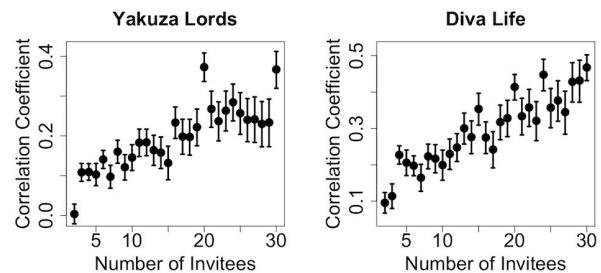


Figure 10 Correlation between *success_rate* and Life Time as indicator of level of engagement

The most significant factor in invitation success is the engagement of the user in the game. Figure 10 presents the correlation between how long users have been playing the game and their *success_rate*, while controlling for the total number of users one invited. We note that there is no trend in *success_rate* over time, that is, users don't tend to improve their efficiency in recruiting new users. It is of course possible that users whose invites are successful tend to play longer because they have friends to play with. Furthermore, the correlation is stronger when users are more active in sending invites. The top 10% of inviters, important to the propagation of FB games, have an average lifespan of 70 days.

By examining both the characteristics of the inviters, and their invitations strategies, we have established that invitation strategy trumps any attributes of the inviters themselves in predicting how successful their invitations will be.

5. Structural Dynamics in Invitation Network

5.1. Collective Effect of Inviters

So far we have focused our analysis on the individual inviter. Next we turn to the invitees, as they interact with potentially multiple inviters, as illustrated by the invitation network in Figure 6 and Figure 8 b). When users join a game after receiving invitations from multiple sources, we can attribute their conversion to a collective effort. We define the *acceptance_rate* to be the ratio of the number of families one invitee joins over all distinct families that user was invited to join. We further examine how a structured group of inviters exerts collective influence over a common invitee.

Figure 11 shows that users are more likely to join as they receive invitations from more inviters. For both YL and DL, the marginal rate is declining and the *acceptance_rate* becomes more saturated.

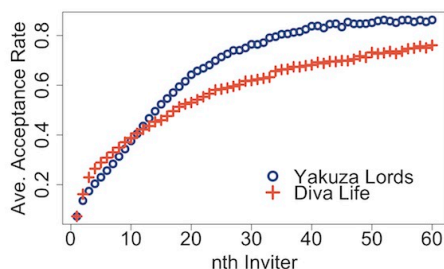


Figure 11 Acceptance rate over different number of invitations received by one user

Heterogeneity of inviter networks: we are interested whether a heterogeneous group of recommenders exerts higher influence over an individual than a more homogeneous group. One might argue that if a user is receiving the same signal to join a game, but the signal is coming from a wide variety of friends, it is more likely to be heeded as the user will perceive the game to be ubiquitous and the advice to join the game independent. To measure the diversity level of a group of inviters that all send invitations to a common invitee, we compute the Shannon’s *entropy*⁴ of FB profiles of this group. Since the number of inviters can influence this measure, we tested the correlation between *entropy* of inviters and *acceptance_rate* of groups of invitees who all received the same number of invites. However the correlation was non-significant.

⁴ $entropy = -\sum_i p_i \log(p_i)$, p_i for example can be the probability of inviters under 20 years old.

Connectedness of inviter network: another feature of the inviter network is how densely the inviters are connected to each other. Since many people did not share their friend lists in FB, we consider the game family network, generated through invitations sent to friends, as a partial projection of the FB social network. We then also control for the total number of inviters to an invitee, and test the relationship between connectedness (CC: clustering coefficient) of inviters and likelihood of adoption. For both games, we find significant positive correlation between the CC of the inviters and the *acceptance_rate* of the invitee (YL: $\rho = 0.21^*$, DL: $\rho = 0.14^*$), which indicates that a more strongly connected game network is more attractive for others to join. Considering the above result, we suspect that social games might be different from other diffusion agents as their utility is primarily in their social function: the utility might be significantly amplified by the social structure it accommodates, rather than its inherent utility as a game. In the next section, we will discuss how the social utility is exerted as one kind of network externality.

5.2. Network Effect of Families in Game

Above we investigated the pointwise features of invitations. We now look at how the adoption takes place from a dynamic perspective: how invitation efficiency varies across time, or different stages of the diffusion network. First we are interested in whether there is a network externality effect in the game contagion in a local community. Family membership can yield both explicit utility such as battle collaboration and implicit benefit by imparting a “feeling of belonging” to players. In fact, we observe that family membership leads to better performance and higher commitment to the game. We hypothesize these different kinds of utilities integrate and accumulate as a network externality as the family size gets larger.

We use the time interval between when the n^{th} and $(n+1)^{\text{th}}$ members join a family to measure the proneness of a new member to join. Figure 12 presents the average time interval for all families that had at least 30 members. On average, the first few members join at increasing speed up to the 7th member, after which time the process slows down as more members join.

The quickening in the joining pattern may be due to a network externality that favors joining a tightly linked family and extracting greater utility within the game from being surrounded by friends. However, after a tightly knit group is readily absorbed, this initial community may find it difficult to acquire new members from its periphery.

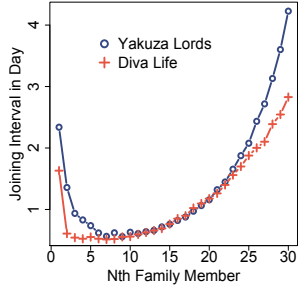


Figure 12 Mean time interval when getting new members into families

5.3. Proximity in Influence

Next we examine how influential inviters are distributed in the social network. In particular, we examine whether influential inviters are clustered or scattered over the network. Thus we measure the similarity in power of influence (*success_rate*) of one inviter with all of her first-degree friends. Figure 13 displays the correlation coefficient between *success_rate* of one inviter and the average *success_rate* of this inviter’s friends who are inviters too. We see that overall there is a strong relationship among proximate inviters. This relationship could arise from three different effects. First, homophily in the social network would tend to place users susceptible to the game close together. Invitations in this region of the network are more likely to be successful. Second, it may be that influential users tend to associate. And finally, and most likely, adjacent users tend to have friends in common, and when inviting the same friend, they share in the outcome.

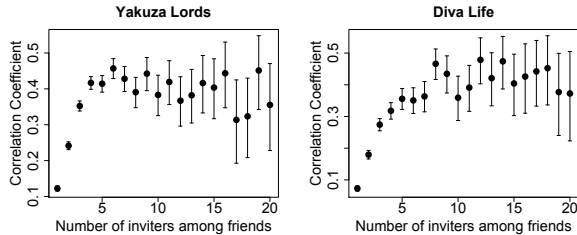


Figure 13 Correlation between one’s *success_rate* and average *success_rate* of one’s friends who invite others

We also examine whether influence carries through the cascade of users joining the game. As Figure 14 shows, firstly, there is a fairly strong correlation between an inviter and her descendants in the cascade over 5 generations. Secondly, we also observe that inviters are similar to proximate offspring nodes in terms of *success_rate*, but this relationship diminishes quickly to around zero the deeper one goes into the diffusion tree.

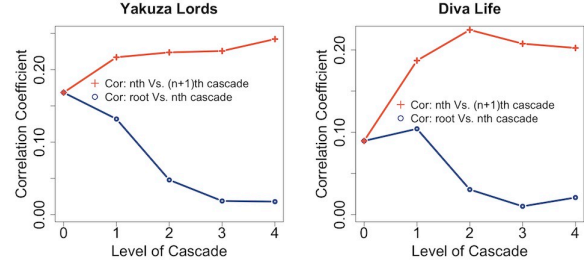


Figure 14 Correlation between one’s *success_rate* and descendants’ average *success_rate* in invitation

6. Discussion and Future Work

In this work, we examine the social dynamics in the invitation and adoption networks of two large social games, Yakuza Lords and Diva Life, both created by Lolapps. As one of the primary features of social games, the invitation mechanism utilizing social networks plays an important role in the propagation of the game. We not only observe the capacity of social games to acquire a huge user base in a short period of time, but find that users who enter the game through a social invitation mechanism are more likely to remain engaged and to successfully invite others.

Thus it is important to understand how these social diffusion processes take place. In general, invitations seem to be made casually: players can simply invite all of their friends who are online at a point in time with a single click. Consequently the number of invitees traces the number of FB friends a user has linearly. On the other hand, due to the sheer number of applications that flood FB users’ newsfeeds with notifications, users can easily experience information overload.

Consequently, the strategies players use to invite others help predict whether the invitations will succeed. Sending fewer invitations, but doing so persistently and spacing them out is more productive than spamming one’s friends indiscriminately. In contrast, users’ profile information and social network attributes do not show much correlation with invitation efficiency. However, while the *success_rate* may not depend on the number of friends, the aggregate number of conversions does: users with more friends have more people to invite. We suspect that the influence exerted through the properties of inviter per se has been overlooked in the push from many FB apps to produce a flood of messages. We would like to continue examining this in our future work.

In addition, we find that if a player was previously invited by another player, or if a player shows more engagement with the game, then she is more likely to suc-

ceed in inviting others. This could result from two inter-linked effects. First, players who like the game might have more insight into who else would also enjoy the game and should be invited. Second, in being invited into the game, users may become more engaged due to the presence of their friends. This network externality effect is apparent as portions of a social network are aggregated into an in-game family. Families rapidly acquire members from densely interlinked portions of the social graph, but their growth eventually slows. This suggests interesting differences in the diffusion of social games relative to other products or services.

Finally, we find that those who are more engaged with the game and successful in influencing others to join, are distributed proximally in both the social network and diffusion cascades. That is, if one is more susceptible to the game and more influential in advocating the game, one's neighbors or parents/offspring tend to be influential as well. Partly this is likely due to friends jointly acting to invite a common friend, and their collective actions being more effective than individual invitations. This suggests the need to identify clusters of potentially susceptible users in the social network where games will diffuse efficiently. In addition, we are interested in how the distribution of susceptibility on the social graph can shape the diffusion process globally. We will analyze this in future work.

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⁵ <http://www.lolapps.com>