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Uncovering the popularity mechanisms for Facebook applications

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HIGHLIGHTS

- For different kinds of Facebook Apps and found that the recent and cumulative popularity play important roles.
- We present a model to regenerate the growth of popularity for different App groups.
- The recent popularity plays more important role in regenerating the popularity dynamics for more popular Apps.
- The cumulative popularity plays more important role for unpopular Apps.

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ABSTRACT

Understanding the popularity dynamics of online application(App) is significant for the online social systems. In this paper, by dividing the Facebook Apps into different groups in terms of their popularities, we empirically investigate the popularity dynamics for different kinds of Facebook Apps. Then, taking into account the influence of cumulative and recent popularities on the user choice, we present a model to regenerate the growth of popularity for different App groups. The experimental results of 917 Facebook Apps show that as the popularities of Facebook Apps increase, the recent popularity plays more important role. Specifically, the recent popularity plays more important role in regenerating the popularity dynamics for more popular Apps, and the cumulative popularity plays more important role for unpopular Apps. We also conduct temporal analysis on the growth characteristic of individual App by comparing the increment at each time with the average of historical records. The results show that the growth of more popular App tends to fluctuate more greatly. Our work may shed some lights for deeply understanding the popularity mechanism for online applications.

1. Introduction

Popularity dynamic plays an important role in online social systems [1]. The mechanisms for online object popularity have been widely studied including movies [2], musics [3], news and other online social collective behaviors [4,5]. Many factors affect the object popularity, such as the internal quality [6], ranking list [7], brand effect [8], recommendation system [9,10], social communication [11,12], and so on [13–15].

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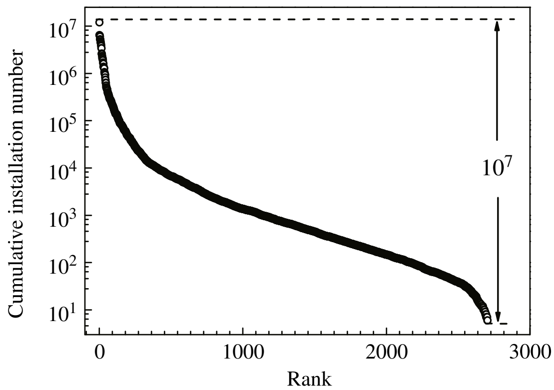

Fig. 1. The number of cumulative installation for 2705 Facebook Apps before August 14, 2007. The vertical axis shows Apps' final cumulative installation number, and horizontal axis reflects the corresponding rank. The difference between the smallest and the largest number of cumulative installation is over ten millions, which indicates the gap in popularities among online Apps.

The preferential selection is regarded as a classic factor on object popularity, which leads to a "rich-get-richer" phenomenon that objects with more cumulative selections also tend to attract more attentions [16,17]. Borghol et al. [18] empirically measured the popularity of videos and found that preferential selection could be used to interpret the video popularity evolution. Szabo et al. [19] found that the long time popularity of online content could be predicted by the early user accesses. Shen et al. [20] introduced the reinforcement Poisson mechanism to model and predict the popularity dynamics. Comparing with the rich-get-richer phenomenon, Bentley et al. [21] introduced a "memory" parameter defined as the number of previous steps which affects an individual's decision. Gleeson et al. [22] investigated the popularity dynamic of the Facebook Apps and found that recent popularity plays more important role.

However, it should be noticed that the popularities of most empirical systems are heterogeneous [23]. Medo et al. [24] found that the citation network exhibits heterogeneous fitness values. For the object popularity of the user-object networks, Liu et al. [25] found that the online user interests could be divided as common interests and specific interests. Furthermore, Ni and Wang et al. [26,27] found that small-degree users tend to select popular movies, while large-degree users prefer to select the unpopular ones. The heterogeneous physics of the object popularity plays an important role for the online social systems evolution [28,29]. As shown in Fig. 1, for the popularity of Facebook Apps, the smallest cumulative installation number is only six, while the largest installation number is over ten millions.

In this paper, we investigate the roles of the cumulative and recent popularities in the popularity mechanisms for Facebook Apps. By dividing the Facebook Apps into different groups in terms of their popularities, we empirically investigate the popularity dynamics of Apps with different popularities and find that the growth rate of more unpopular Apps fluctuates more randomly in the initial period, and the growth rate of all App groups finally stabilizes around 1. Then, we present a model to regenerate the popularity dynamics of the empirical Facebook Apps, and find that as the Apps popularities increase, the recent popularity plays more important role. Finally, we conduct temporal analysis on the growth characteristic of each App by comparing the increment at each time step with the average installation time of historical records, which show that the growth of online Apps is fluctuant and the growth of more popular App fluctuates more greatly.

2. Empirical analysis

In this section, we analyze the popularity dynamics for different kinds of Apps by dividing Facebook Apps in terms of their popularity [30]. Firstly, we introduce the definitions to measure Apps' popularities [22]. To measure the change in number of cumulative installation for App i at time t, the increment $f_i(t)$ can be denoted by

$$f_i(t) = n_i(t) - n_i(t-1), \tag{1}$$

where $n_i(t)$ is the total number of users who have installed App i by time t.

To compare the popularities of different Apps when they are the same age (i.e., the same number of time steps after they were launched), the age-shifted increment $\widetilde{f}_i(a)$ was introduced to measure the change in cumulative installation number for App i at age a, which is defined as $\widetilde{f}_i(a) = \widetilde{n}_i(a) - \widetilde{n}_i(a-1)$, where $\widetilde{n}_i(a) = n_i(t_i + a)$ is the cumulative installation number of App i during a time steps after its launch time t_i. In order to present the popularity dynamics for a group of Apps, the mean scaled age-shifted growth rate $r(a)$ can be defined as

$$r(a) = \langle \frac{\widetilde{f}_i(a)}{u_i} \rangle_Z, \tag{2}$$