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As objects become popular gradually, they are more likely accepted by small-degree users but lose attention among the large-degree users.

Popularity and User Diversity of Online Objects

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Abstract

The popularity has been widely used to describe the object property of online user-object bipartite networks regardless of the user characteristics. In this paper, we introduce a measurement namely user diversity to measure diversity of users who select or rate one type of objects by using the information entropy. We empirically calculate the user diversity of objects with specific degree for both MovieLens and Diggs data sets. The results indicate that more types of users select normal-degree objects than those who select large-degree and small-degree objects. Furthermore, small-degree objects are usually selected by large-degree users while large-degree objects are usually selected by small-degree users. Moreover, we define the 15 percent objects of smallest degrees as unpopular objects and 10 percent ones of largest degrees as popular objects. The timestamp is introduced to help further analyze the evolution of user diversity of popular objects and unpopular objects. The dynamic analysis shows that as objects become popular gradually, they are more likely accepted by small-degree users but lose attention among the large-degree users.

Key words: Popularity, User diversity, Online objects.
PACS: 89.75.Hh, 89.20.Hc, 05.70.Ln

1 Introduction

Popularity dynamics has attracted much attention for online systems [1–5]. Especially in online e-commerce systems, the object popularity is of great significance as it may reflect the potential demand for an object in the future [6]. That is to say, the more popular the object is, the higher attention the consumers pay on it [7].

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Prior works on measuring the object popularity have focused on the number of hyperlinks pointing to a document [8], the number of times the object has been downloaded or purchased [9] and the number of times a video is watched or commented [10]. Park $et\ al$ [11] found that consumers were more or less affected by the quantities of reviews that reflected the level of popularity. Hu $et\ al$ [17] gave an opinion that popular objects could get hundreds of reviews at some large merchant sites which indicated that they were prevalent. In addition, the popularity of objects have been analyzed and utilized in the personalized recommendations [12–16]. Ahn $et\ al$ [18] proposed a three-dimensional model of popularity to develop popularity classes of objects in recommendation algorithms. Liu $et\ al$ [19] argued that the initial recommendation power located on the objects ought to be determined by their degree and the users tastes that the degree of objects represented the popularity of objects. Further, object popularity has also been widely detected in commercials [20] and social media [21]. So it is of great significance to recognize the object popularity more precisely.

However, existing manifestations including the quantities of views or degrees indicate the popularity outwardly [22], regardless of the fact that these objects could be accepted by distinct kinds of users [23], which could be defined as a supplementary form to consider the popularity. In this paper, we introduce a measurement, namely user diversity, to show what kind of objects are chosen by various types of users. The information entropy [24], a concept of measuring the amount of the information, is used to measure the information with respect to users' collective behaviors. The greater the entropy is, the more uncertain the user behavior is. Inspired by this idea, we introduce the information entropy to measure the user diversity. We consider that the information entropy of the users who select the objects with specific degree could indicate the user diversity of the objects. The MovieLens and the Diggs data sets are investigated in this paper. Then we classify all the objects according to the their degrees in two data sets, respectively. Then the user diversity of objects with specific degree are calculated respectively. We calculate the average degree of users who select the objects with specific degree to find what type of users would choose these objects. Empirical findings can be drawn from the results: Firstly, more types of users select normal-degree objects than those who select large-degree and small-degree objects. Secondly, small-degree objects are usually selected by large-degree users while large-degree objects are usually selected by small-degree users. Furthermore, we sort all the objects according to their degree from small-degree to large-degree, selecting two groups which consist of the objects with largest degrees and smallest degrees respectively. Next we normalize the lifespan of all the objects that are ordered by time in two groups, dividing their lifespan into twenty time intervals of the same length. The user diversity of objects of each time interval of their lifespan in both groups are finally calculated.

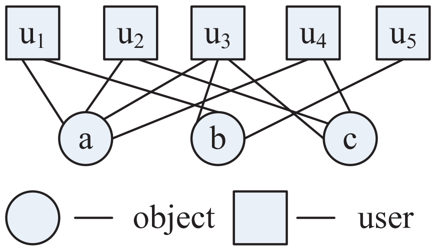

Fig. 1. Suppose there are 3 objects whose degree are 4, 3, 3 respectively in a user-object bipartite network. The degrees of the users u_1, u_2, u_3, u_4, u_5 are 2, 2, 3, 2, 1 respectively. For the objects with degree 3, We can find that the user with degree 1 selects once, the users with degree 2 select three times, and the user with degree 3 selects twice, so the total number is 1+3+2=6. The probability distribution is $(\frac{1}{6}, \frac{1}{2}, \frac{1}{3})$, thus the user diversity $V(3) = \frac{\frac{1}{6}\log_2 6+\frac{1}{2}\log_2 2+\frac{1}{3}\log_2 3}{\log_2 3} = 0.9206$. For the object with degree 4, the users with degree 2 select three times, and the user with degree 3 selects once, so the total number is 3+1=4. The probability distribution is $(\frac{3}{4}, \frac{1}{4})$, thus the user diversity $V(4) = \frac{3}{4}\log_2\frac{4}{3} + \frac{1}{4}\log_2 4 = 0.8113$.

2 Methods

The information entropy presented by Shannon [24] is used to calculate the expected value of the information contained in a message which is proposed to describe the uncertainty of the source. The more orderly a system is, the lower the information entropy would be; On the other hand, the more uncertain the system is, the higher the information entropy would be. So the information entropy can be defined as a variable to describe the uncertainty of information.

Suppose we have a set of n events whose probabilities of occurrence are $\alpha_1, \alpha_2, \ldots, \alpha_n$. Then the information entropy, defined by P, can be expressed as

$$P = P(\alpha_1, \alpha_2, \ldots, \alpha_n) = \sum_{l=1}^{n} \alpha_l \log_2 \alpha_l^{-1}, \tag{1}$$

where $\alpha_l \geq 0 (l = 1, 2, \ldots, n)$ and $\sum_{l=1}^{n} \alpha_l = 1$.

The definition of the information entropy in our paper is a bit different. In this paper, we apply it to measure the user diversity of objects with different degrees. With the purpose of comparing the user diversity of objects citing the results since the original results are different, we standardize the results by utilizing the characterization of maximum [26,27]. Then the equation can be expressed as,

$$V(\rho) = \frac{\sum_{l=1}^{n(\rho)} \alpha_l \log_2 \alpha_l^{-1}}{\log_2 n(\rho)}, \tag{2}$$

where ρ denotes the object degree, $V(\rho)$ indicates the user diversity of objects with degree ρ. The possibility α_l represents the probability that the users with specific degree contained in all the users who select the objects with degree ρ. In addition, the variable $n(\rho)$ denotes the number of users with different degree who select the objects with degree ρ. The values of user diversity $V(\rho)$ we get are all between 0 and 1.

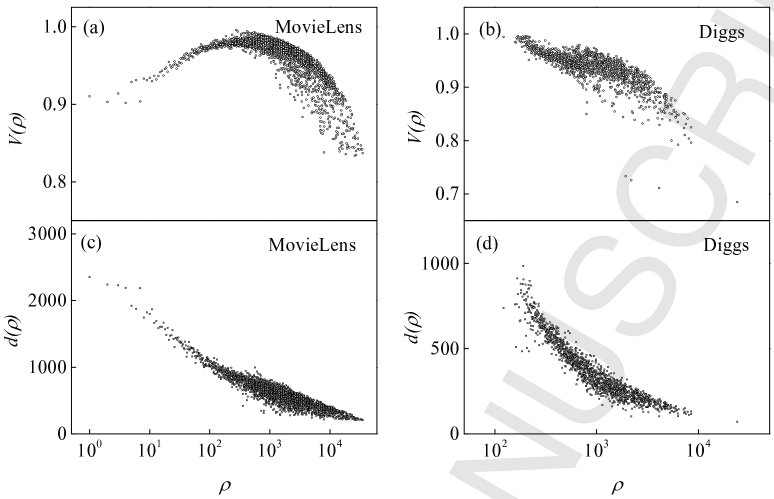

Fig. 2. The correlation between the object degree ρ and the user diversity $V(\rho)$ for the MovieLens and Diggs data sets, respectively. And the correlation between the object degree ρ and the average degree $d(\rho)$ of the users who select the objects with degree ρ. The user diversity V has been standardized because it is clear and easier to be measured.

All the selection information of the objects with a specific degree are collected, and the calculation process of the user diversity $V(\rho)$ is shown in Fig. 1.

As is shown in Fig. 1, we calculate the selection information of the users who select the objects with degree 4, 3, 3. The users are divided on the basis of degree in this paper. The user diversity of the objects with degree 3 is 0.9206 and that of the object with degree 4 is 0.8113. We can find that more types of users select objects with degree 3 than that with degree 4. Furthermore, we consider an object with diverse popularity if the object is selected by users with different degrees. With respect to the original definition of information entropy, we know that the larger the user diversity is, the more diverse the users would be, which means that the objects are selected by more types of users with a higher attention.

Then we need to consider what kind of users would prefer the objects with specific degree respectively. The degree of user i, denoted by k_i, is defined as the number of objects the user i selects. A user-object network can be revealed as an adjacent matrix $\mathbf{A} = \{a_{ij}\} \in R^{N,M}$. If u_i selects the object o_j, the a_{ij}=1, and a_{ij}=0 otherwise. Then we define the equation of the average degree $d(\rho)$ of the users which can be expressed as,

$$d(\rho) = \frac{\sum_{j\in\delta(\rho)} \sum_{i=1}^{N} a_{ij} k_i}{\sum_{j\in\delta(\rho)} \sum_{i=1}^{N} a_{ij}} \tag{3}$$

where N is the total number of users while M is the total number of objects in the network, $j \in \delta(\rho)$ means the object o_j belongs to the set of objects with degree ρ

while k_i represents the degree of user u_i.

3 Empirical analysis

Table 1
Basic statistics of the MovieLens and Diggs data sets, where N, M and E denote the number of users, objects and edges, respectively.

Data Sets	N	M	E
MovieLens	69,878	10,677	10,000,054
Diggs	139,409	3,553	3,018,197

In this paper, we empirically analyze two real data sets, named MovieLens and Diggs data sets. The MovieLens is a movie rating Web site where users can rate movies and receive personalized recommendations. The Diggs Web site aggregates the stories specifically for the Internet audience such as science, trending political issues, and viral Internet issues. The main purpose of the Diggs is to play the part of a massive collaborative filtering tool to select and show the most popular content, so the registered users can choose submissions they find attractive [25]. The basic statistics are shown in Table 1.

According to the object degree ρ, we classify the objects of both data sets into different groups respectively, because the objects with the same degree can be regard as the same type of objects since they are as popular as each other. All the users who select the objects with specific degree are collected. Then we calculate the user diversity of objects with degree ρ. By using the equation (2), the user diversity $V(\rho)$ can be easily worked out. The empirical results show that the value of $V(\rho)$ in the MovieLens data set ranges from approximately 0.83 to 1, while in the Diggs data set it ranges from about 0.7 to 1. Since the results in two data sets are relatively different from each other, the average degrees $d(\rho)$ of the users who select the objects with degree ρ are calculated by using the equation (3).

As shown in Fig. 2(a) and Fig. 2(b), we can find that in the MovieLens data set, the user diversity $V(\rho)$ would increase from 0.9015 to the largest value 0.9955 when the object degree ρ lies in the range from 1 to 275. And then it falls as the object degree increases. However, the results in the Diggs data set are relatively different. We can find that the user diversity $V(\rho)$ decreases as the object degree ρ increases. In addition, from Fig. 2(c) and Fig. 2(d), the average degree $d(\rho)$ of the users who select the object with degree ρ decreases as the object degree ρ increases in both two data sets. It should be noted that the difference between phenomena results from the distinction between two data sets. In the MovieLens data set, the decreasing of the user diversity $V(\rho)$ of large-degree objects as the object degree increases shows that the increasing of the object degree can not receive more concentration

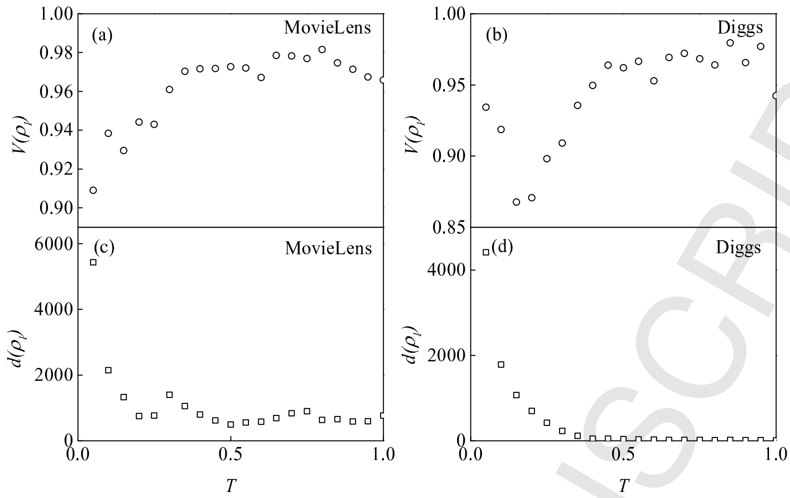

Fig. 3. The correlation between the lifespan T of the popular objects and the user diversity $V(\rho_1)$ as well as average user degree $d(\rho_1)$ of the users who select popular objects for the MovieLens and Diggs data sets. The lifespan when the objects stay in the system is scaled to the interval [0,1] and is separated to 20 sub-intervals of the same length.

among all types of users. On the contrary, the users of various types represented by their different degree prefer normal-degree objects to large-degree and small-degree objects. In the Diggs data set, users' attention decreases as the objects degree ρ increases. Normal-degree objects are accepted by most various types of users but large-degree objects are chosen by least various types of users. Combining with the trend of the average degree $d(\rho)$ of users, we can find that the numerical value of average degree $d(\rho)$ of users who select small-degree objects is greatly larger than those who select large-degree objects, indicating that large-degree objects are usually selected by small-degree users while small-degree objects are usually selected by large-degree users.

4 Effect of the timestamp on the user diversity

Since some objects may be popular for a lifetime while others can fade away in short periods, the popularity of the objects changes continuously [28]. At this point, it is important to investigate how the user diversity $V(\rho)$ of these objects evolve with time. Firstly, the timestamp is introduced to represent the lifespan of the objects. Each object's lifespan is normalized into the same time interval [0, 1], where 0 and 1 represent the starting and ending time of the object's activities respectively. Then we divide the normalized lifespan into 20 time intervals of the same length. To ensure the accuracy of the results that the objects mentioned should be selected by enough times during their lifespan, we only take objects whose degree ≥ 20 into consideration. Secondly, object degrees are sorted from small-degree to large-degree. We define the ten percent objects of largest degrees as popular objects while

$V(\rho_1)$ and $d(\rho_1)$ represent the user diversity of these objects and average degree of users who select them respectively. We define the fifteen percent objects of smallest degrees as unpopular objects while $V(\rho_2)$ and $d(\rho_2)$ represent the user diversity of these objects and average degree of users who select them respectively. Considering that the degrees are small, more percent of smallest-degree objects are chosen. Then we analyze the evolution of user diversity $V(\rho_1)$ and $V(\rho_2)$ of popular and unpopular objects of each time interval. In each time interval, we respectively collect all the selecting records by the users and then make the calculation.

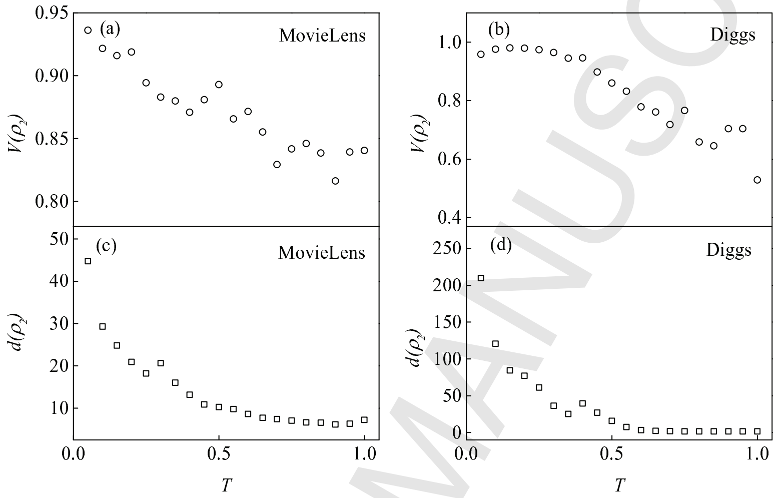

Fig. 4. The correlation between the lifespan T of the unpopular objects and the user diversity $V(\rho_2)$ as well as average user degree $d(\rho_2)$ of the users who select unpopular objects for the MovieLens and Diggs data sets. The lifespan when the objects stay in the system is scaled to the interval [0,1] and is separated to 20 sub-intervals of the same length.

The results for the user diversity $V(\rho_1)$ of large-degree objects during their lifespan are respectively shown in Fig. 3(a) and Fig. 3(b), from which we can find that in the MovieLens data set, as the time since the objects enter the system becomes longer, the numerical value of $V(\rho_1)$ increases from 0.9090 to 0.9816 when T=0.8 and then begins to fall. In the Diggs data set, the numerical value of $V(\rho_1)$ of the popular objects decreases from 0.9343 to 0.8677 when T=0.15, but in the rest of time, it begins to increase. Besides, the range of variation of $V(\rho_1)$ for the Diggs data set is larger than that for the MovieLens data set. From Fig. 3(c) and Fig. 3(d), the average degree $d(\rho_1)$ of users in both two data sets continues to decrease during the objects' lifespan. The difference may result from the distinction between two data sets. In combination with the trend of the average degree $d(\rho_1)$ of users in Fig. 3(c) and Fig. 3(d), popular movies in the MovieLens data set may attract increasingly more types of users at the time beginning but as the time passes, large-degree users would not like to select popular movies again which makes the user diversity $V(\rho_1)$ decrease. The user diversity $V(\rho_1)$ of the popular stories in the Diggs data set becomes smaller at first because large-degree users in the Diggs data set may not prefer these objects when they become popular. But as the stories become popular, more types of small-degree users select the stories and the user diversity $V(\rho_1)$ increases.

The evolution of the user diversity $V(\rho_2)$ of small-degree objects in different data sets are shown in Fig. 4(a) and Fig. 4(b). We can find that in the MovieLens data set, $V(\rho_2)$ decreases from 0.9361 to 0.8161 across the objects' lifespan. In the Diggs data set, $V(\rho_2)$ also decreases from 0.9802 to 0.5284 across the objects' lifespan. From Fig. 4(c) and Fig. 4(d), the average degree $d(\rho_2)$ of users continues to decrease as the time passes, while the trend of the average user degree is similar to that of the MovieLens data set. We find that because of the different characteristics between two systems, the value of user diversity $V(\rho_2)$ in the Diggs data set decreases far more sharply than that in the MovieLens data set. Combining with average degree $d(\rho_2)$ of user, we find that as the time goes by, fewer types of users choose unpopular objects. The reason why these projects are not acceptable by different sorts of users as the time files may be that they are low-quality objects. Another point is that the user diversity $V(\rho_2)$ of unpopular objects about stories decreases more sharply than those about movies. This could be explained that no matter how unpopular the object is, movies are more acceptable than stories among various types of users.

5 Conclusion and discussions

In order to consider what kind of users would prefer the objects with specific degree, we introduced a supplementary measurement, namely user diversity, denoted by $V(\rho)$, to describe how diverse of users who selected the objects with degree ρ. Then the average degree $d(\rho)$ of users who select these objects were also calculated. The empirical results indicated that more types of users select normal-degree objects than those who select large-degree and small-degree objects. Furthermore, we found that large-degree objects were usually selected by small-degree users while small-degree objects were usually selected by large-degree users. Moreover, we analyzed the evolution of the user diversity $V(\rho_1)$ and $V(\rho_2)$ of popular objects and unpopular objects, respectively. Fifteen percent objects of smallest degrees were defined as unpopular objects while ten percent ones of largest degrees were defined as popular objects. By introducing the timestamp, we found that in the MovieLens data set, the user diversity $V(\rho_1)$ of large-degree objects increased in the early time intervals of their lifespan and then turned to decrease, while in the Diggs data set, the user diversity $V(\rho_1)$ of large-degree objects decreased at first and then turned to increase. Besides, the user diversity $V(\rho_2)$ of small-degree objects maintained decreasing during their lifespan in both systems. Another point was that the user diversity $V(\rho_2)$ of stories decreased sharply than those about movies. In combination with analyzing the users with average degree $d(\rho_1)$ and $d(\rho_2)$ of users who selected these popular and unpopular objects, we concluded that the popular objects were most likely to be selected by small-degree users while unpopular objects were selected by fewer types of users gradually. This might because a small-degree user likes popular movies for he/she does not have enough experiences. As the time goes by, he/she cultivates and loses interest in popular objects, being a large-degree user, and has motivation to select objects that may cater his/her interest. To sum up, a research on user diversity $V(\rho)$ may be useful to analyze users' online behavior.

All in all, online popularity has enormous impact on different domains which is of great research importance on practical application [29]. We have introduced the concept of user diversity $V(\rho)$ and investigated the diversity of users who select objects with specific degree to give a supplementary form about popularity. However, our effort is still far away from totally understanding the online popularity. We have only sorted objects and users by degree without considering other factors, which may classify the users and objects from various angles. In addition, we have not investigated the constitution of the types of users who select the objects with specific degree, which is a still an open question. Furthermore, it is important to verdict whether the information entropy could be considered in the recommender algorithms [30–33].

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