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Measuring the Mobile App Market: A Complex Network Approach

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Abstract: Online marketplaces of mobile applications have undergone dramatic growth in recent years, as exemplified by Apple AppStore and Google Android Market. However, systematical observation and analysis of such a market are still missing. Therefore, this study seeks better understanding of such marketplaces by measuring one of them, i.e., the Google Play Market, from various perspectives. Since this market has grown to a complex system with large amount of applications, this study measures it from the scope of complex networks. To this end, this study first constructs two app relationship networks and one user navigation network based on the data set crawled from the Google Android Market. This study then generates both micro-scope and macro-scope statistics and analysis on various essential metrics of those three networks. By this way, this study is in the purpose of revealing both the relationships among applications and the influences imposed on the user behaviors by the market. To the best of the knowledge, this study is the first to observe, analyze the mobile application market, especially from the view of complex network. Results of this study can serve as data supports for various future researches on mobile apps, which is a rising and problem abundant area in the era of mobile computing.

Key word: Mobile app android market, complex network, measurement

INTRODUCTION

The mobile computing boom is in full swing. Online marketplaces of mobile application, e.g., the Google Android Market and the Apple AppStore, have been launched for users to meet their needs for all kinds of mobile applications. These markets are undergoing tremendous expansion in recent years. Take Google Android Market for example, since its announcement on August 28, 2008, it has raised an explosive growth during these years, both on the number of applications and the popularity of publishers. Till recently, it has topped the milestone of 700,000 active applications (Cnet, 2013).

Such dramatically growing online application markets and their increasing amount of applications not only serve opportunities but also call for better understanding of the mobile apps, user behaviors and market ecosystems. Recently, Girardello and Michahelles (2010), Yan and Chen (2011) and Lim *et al.* (2011) have proposed recommendation solutions to alleviate the application discovery problem in online markets. Holzer and Ondrus (2011a) and Henze and Boll (2011) took a developer's perspective to explore the trends which will impact the development of markets and to investigate the proper release time for applications. Muller *et al.* (2011) made a comprehensive comparison of the business models of seven popular mobile app stores. Campbell and Ahmed (2011) presented an assessment of the mobile OS-centric ecosystems. Moreover, these marketplaces have gathered large scale of user data for researchers (Cramer *et al.*, 2011; Henze and Boll, 2010, 2011; Yan and Chen, 2011). However, there still lacks a systematic and large scale study of such markets, especially measurements on what statistical features they retain and how they affect the application discovery of mobile users.

For the above reason, this study aims to take a look at the online markets on both the relationships among applications and their navigation effects on the users. Main efforts and contributions of this study are as follows:

- It initially crawls real data from the Google Play market and construct three complex networks based on the data set. Such networks are constructed to capture the relationships among mobile applications as well as the navigating effects on users placed by the online market
- It originally conducts multilevel measurements of the three networks. Such measurements reveal their characteristics as complex networks, including the scale-free degree distribution, the clustering tendency, the small average shortest path length and the feature of community structure

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- It specifically generates analysis of the application market based on its network measurements, which help to gain better understanding on both the relationships among applications and its possible effects on the online behaviors of users

The measurements, observations and analysis in the study provide original insights to the inner relationship among applications, the marketing features of android ecosystem and the influences placed by the android market on user behaviors. Such findings are expected to fundamentally guide the recognition, design, development and evolution of the android market. To the best of the knowledge, this study is the first to take a complex network approach to systematically measure and analyze the android market. It is worth noting that although this study focuses on the Google Android Market, the methodologies developed can be easily applied to other online mobile app markets.

The reminder of this study firstly presents the related works. It then describes the data set crawled for this study. Following that it presents the statistics and analysis of the app relationship networks and the user navigation network, respectively. Finally, conclusions are drawn for this study.

Complex network research can be tracked back to pioneering works of Flory (1941), Rapoport (1951, 1954, 1957) and Erdos and Renyi (1959, 1960, 1961). It has been particularly contributed by the small-world concept (Watts and Strogatz, 1998), scale-free models (Barabasi and Albert, 1999) and the community identification methods (Girvan and Newman, 2002). Afterward, the structure and dynamics of various natural and human-made networks have been studied (Albert and Barabasi, 2002; Rubinov and Sporns, 2010; Newman 2003b; Boccaletti *et al*., 2006) along with the development of complex network theory (Lancichinetti and Fortunato, 2009; Shanker, 2010). However, the online marketplaces with huge amount of applications have not been characterized before. Therefore, this study not only constructs the complex networks of mobile apps but also originally characterizes and measures them from multiple levels and scopes.

The prior studies about mobile application marketplaces mostly focused on the business models from a variety of perspectives (Muller *et al*., 2011; Tuunainen *et al*., 2011; Holzer and Ondrus, 2011b). Recently, they capture interests from research community by their explosive growth and usage as distribution channels for gathering large scales of user feedbacks (Cramer *et al*., 2011; Henze *et al*., 2011). Meanwhile, some work has paid attention to the application recommendation (Girardello and Michahelles, 2010; Lim *et al*., 2011; Yan and Chen, 2011) and promotion (Henze *et al*., 2010). Little effort, however, has been paid to the systematical observation and analysis of online markets. Not to mention the measurements based on a large scale of real data. Furthermore, there is little literature which has introduced the complex network to investigate the online markets of mobile applications, which is filled by this study.

DATA SET

To support this study, web pages of 104303 applications have been crawled from the website of Google Play Market. Start points of the crawling include the popular applications, the latest applications and randomly selected applications. Such applications concurrently serve as the start points of accessing the online market by most of the users. The crawling stops when there are no more new applications following the application links on the webpages. Such a process guarantees that the data set would cover applications accessed by most users at most time. The results of measurements thus are expected to be reliable.

Each webpage crawled for an application contains a wide range of information, e.g., the descriptions, reviews and permissions. To conduct the measurements, specific app features are extracted from the webpages to characterize each application, which are listed in Table 1 along with their descriptions. Specifically, there are several "alsoview" and "alsoinstall" links on the webpage of each application, which serve as selected application recommendations. It is defined that there is an "alsoview" or an "alsoinstall" relationship between two applications when one of them is recommended to another by "alsoview" or "alsoinstall" links, respectively.

Table 1: Application characterized features

Feature	Description
Id	Identification of application
Category	Category of application
Price	Free or the price of application
Current version	Version of application
Size	Size of application
Updated	Date when application updated
Installs	Quantity of users who installed this application
Ratings	Ratings scores and their corresponding votes
Content rating	Rating of content maturity
Alsoview	Applications user who viewed this application also viewed
Alsoinstall	Applications user who installed this application also installed
Requires android	Version requirement of application

APP RELATIONSHIP NETWORK

Study of this section measures the relationship among applications. To this end, two kinds of application relationship networks, i.e., the "alsoview" network and the "alsoinstall" network are constructed. These two networks are derived from the relationships among applications, which are featured with "user viewed this application also viewed" and "user installed this application also installed", respectively.

CONSTRUCTION OF NETWORKS

Details of Google's recommendation methods for each alsoview and alsoinstall applications keep unknown to the public. It is assumed that both the alsoview and the alsoinstall relationships are symmetry ones by the semantic understanding. Thus both networks are constructed using the undirected graph methods. In such two networks, each node denotes an application and an edge denotes an alsoview or alsoinstall link crawled from the websites.

According to the common definitions of complex networks, the alsoview and the alsoinstall networks are denoted by G_v and G_i, respectively. Nodes and edges of them are defined by sets of $N(G_v)$, $E(G_v)$ and $N(G_i)$, $E(G_i)$, in which each node $v_v \in N(G_v)$ or $v_i \in N(G_v)$ is an application identified by its application id and each edge $e_v \in E(G_v)$ or $e_v \in E(G_v)$ is the relationship "alsoview" or the "alsoinstall", respectively. The sizes of the two networks can be identified by the number of their nodes and edges, as listed in Table 2.

General statistics: To systematically reveal the relationship among applications, this section measures the two networks from the node level to the network level. It leverages several mainstream metrics including those fine-grain and coarse-grain ones. Based on these quantitative indicators, the investigation further explains the possible causes behind them.

Node level: Given a single application, it is usually cared how many applications are connected to it, which means how many applications are related to it in terms of the user behaviors. To generate such a measurement, this study leverages the metric of node degree and lists the results in Table 2. To gain a global view of this metric, it further measure the distribution of it across the whole network, which is illustrated in Fig. 1. The distribution of node degree determines an important feature, called scale-free, in complex networks.

From Fig. 1 and Table 2, it can be derived that although the android online market provides only four related applications for an application by each

Table 2: Statistics and measurements of app relationship networks

Statistics and measurement	G_v	G_i
No. of nodes	103324	103318
No. of edges	380224	345320
Degree with max nodes	4, 54666	4, 36540
Max degree	492	154
Average degree	7. 3598	6.6846
Average clustering coefficient	0.216	0.239
No. of components	201	159
No. of isolates	192	155
Ratio of isolate nodes	0.185%	0.150%
Diameter	14	39
Average shortest path length	5.730	10.777

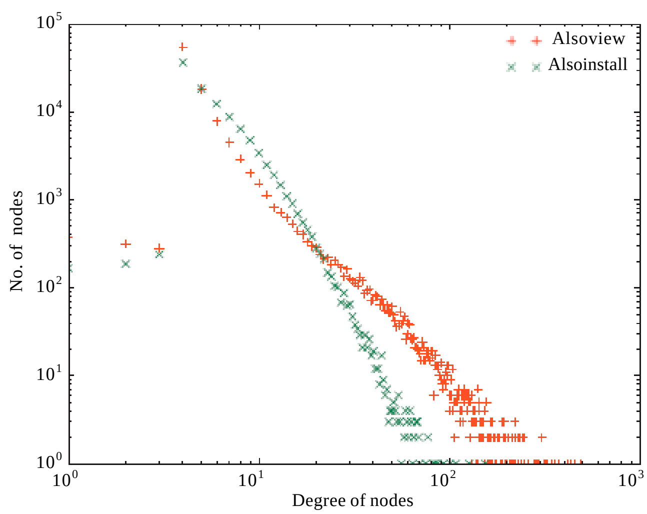

Fig. 1: Degree distributions in app relationship networks

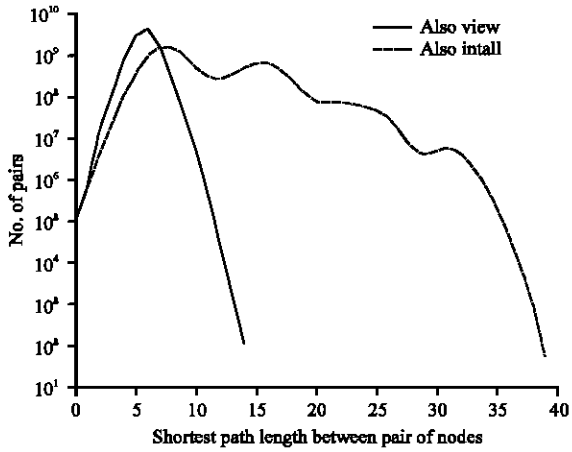

Fig. 2: Distributions of shortest path length between node pairs in app relationship networks

relationship, there still are a few nodes with extreme large degree while a majority of nodes have small one. That is, there are popular applications that are connected by a large amount of applications based on user behaviors across the whole market.

Dyad level: The bilateral relationship between nodes in network primarily depends on their connections. Such connections can be identified using the path between them. Hence, measurements in this section are generated based on the path between two nodes. To be specified, this section investigates the length of the shortest path between each pair of nodes, which indicates how close the two applications are with each other.

Since some nodes in networks may be isolated from others, the length of shortest path for the node pairs, which include at least one reachable path between them, is examined. The results are illustrated in Fig. 2. It shows that the maximum and average distances between applications are much smaller in the alsoview network than that in alsoinstall network. It suggests that the viewing behaviors of mobile users are more concentrated than the installing behaviors. This may result from that viewing is more freely but installing needs more efforts so that users are more cautious on the installing than just viewing.

Triple level: On the triple node level, this study investigates the clustering coefficient of network which is the measure of degree to which neighbors of a node tend to connect together. This tendency has been observed in most real-world networks, especially in social networks (Watts and Strogatz, 1998). Therefore, examine whether such a feature also exists in the application relationship networks.

This part of measurements takes the definition of clustering around a node *v* as the number of triangles in which the vertex *v* participates normalized by the maximum possible number of such triangles:

$$c_v = \frac{2T_v}{d_v(d_v - 1)} \qquad (1)$$

where, T_v is the number of triangles through the node *v* and d_v is the degree of the node.

It can be derived from the average clustering coefficient in Table 2 that weak clustering tendency exists in both app relationship networks which may attribute to the intrinsic similarity between applications related to the same neighbor. Meanwhile, it concurrently suggests that users are find more novel applications.

Community level: One of the most important features of complex networks is the community structure, which has been empirically found in many real technological, biological and social networks. Furthermore, its emergence seems to be at the heart of the network formation process.

A community is a group of nodes with most edges inside groups and few edges between them. Particularly, when no edge exists between communities, the network is broken up to components. This study leverages the community detection methods from (Blondel *et al*., 2008) and generates communities which maximize the modularity using the Louvain heuristics. As shown in Table 2, isolate nodes count large proportion of the communities. Hence, only several largest components are reported in Fig. 3.

It illustrates that there are less than 10 communities that are not isolated in G_v and G_i. More precisely, the network of alsoinstall relationship has only 4 such communities while the number of such communities in the network of alsoview relationship is 9. Furthermore, it is revealed that almost all nodes are included in the largest community which covers 103094 nodes out of 103324 nodes in the alsoview network and 103130 nodes out of 103318 nodes in the alsoinstall network. This observation indicates that almost all applications are related in terms of the viewing and installing behaviors. This may result from the large population of online users, which makes the experiences of other users valuable to alleviate the application discovery.

Network level: On the network level, this study considers two metrics which play important roles on characterizing the internal structure of network, especially in measurement of separation between two nodes. They are the network diameter and the average shortest path length. The network diameter indicates the largest length

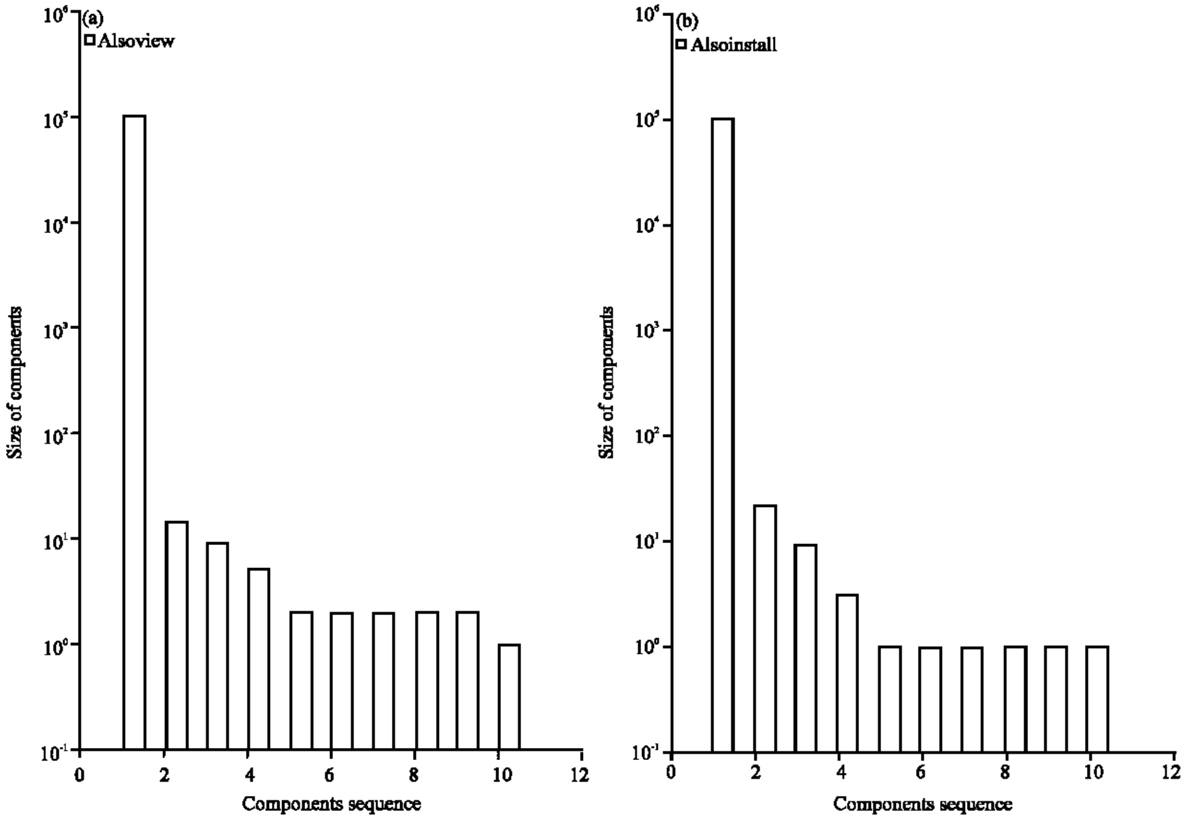

Fig. 3(a-b): Size of top 10 components in app relationship networks (a) Alsoview and (b) Alsoinstall

among the shortest paths of node pairs. The average shortest path length denotes the average length of the paths between all node pairs.

The android market doesn't provide related applications for some applications. Thus not all the nodes in the relationship networks are connected to each other. This study defines the network diameter as the diameter of the largest connected component and the average shortest path length as the average of all distances between connected nodes. As shown in Table 2, the average shortest path length of the alsoview network is much smaller than that of the alsoinstall network. Such quantitative results demonstrate that in app relationship networks, applications that are connected more closely by the viewing behavior but looser by the installing behavior. This may also attribute to the reason that installing takes more efforts than viewing.

Advanced measurements: This part of study takes further analysis in this section to better understand the users' preferences and consumption habits, which may influence the developing and marketing decision of applications. It examines problems such as which kinds of applications are popular, how the price of application affects users' installations and why applications are related to each other in terms of users' viewing or installing behavior. The measurements and analysis are conducted from two perspectives, i.e., the measurements of applications and that of relationships.

Measurement of applications: As for applications, this section investigates the price distribution of applications, the popularity across different categories and the relationship among application installations, prices and ratings. Among them, the price distribution plays an indicator to the marketing feature of android ecosystem; the popularity across categories of applications reveals the taste of users. Furthermore, the relationship among installations and the price and rating of applications exposes the acceptance of users against the expectation of developers.

Price distribution: As shown in Fig. 4, the price distribution indicates that in android market there are much more free applications than paid applications and those paid applications concentrate their prices in a narrow range. The reason may be uncovered by Fig. 5, which suggests that most consumers tend to install

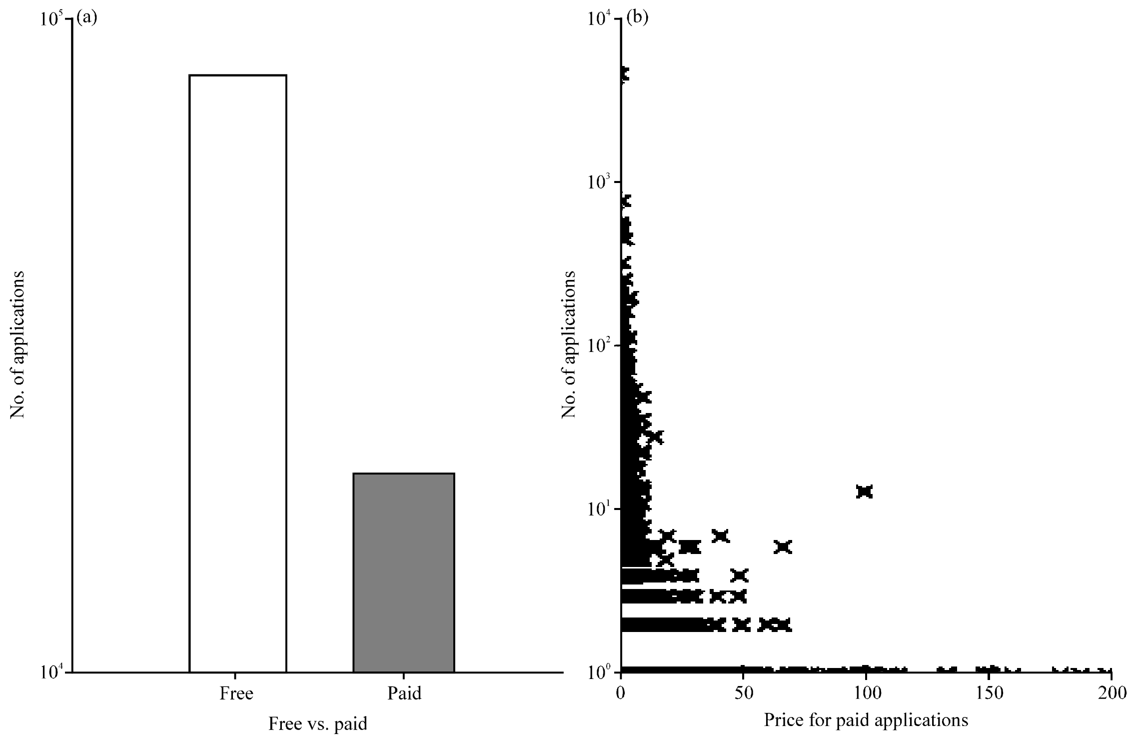

Fig. 4(a-b): Comparison of (a) Free and paid applications and (b) Price distribution of paid applications

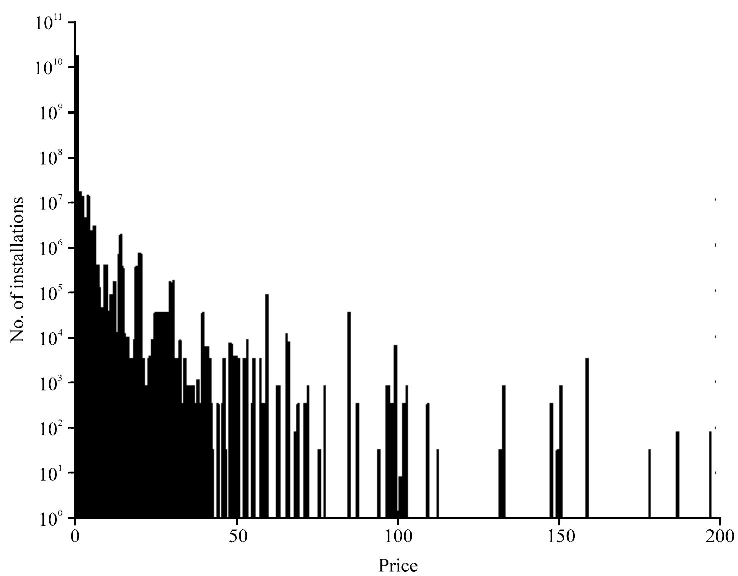

Fig. 5: Installation distribution across prices

applications of low price, which may serve as an important indicator for the design and development of online app markets.

Installations across categories: To find which category of applications are of the most popular, come top 5 categories which occupy the most installations are

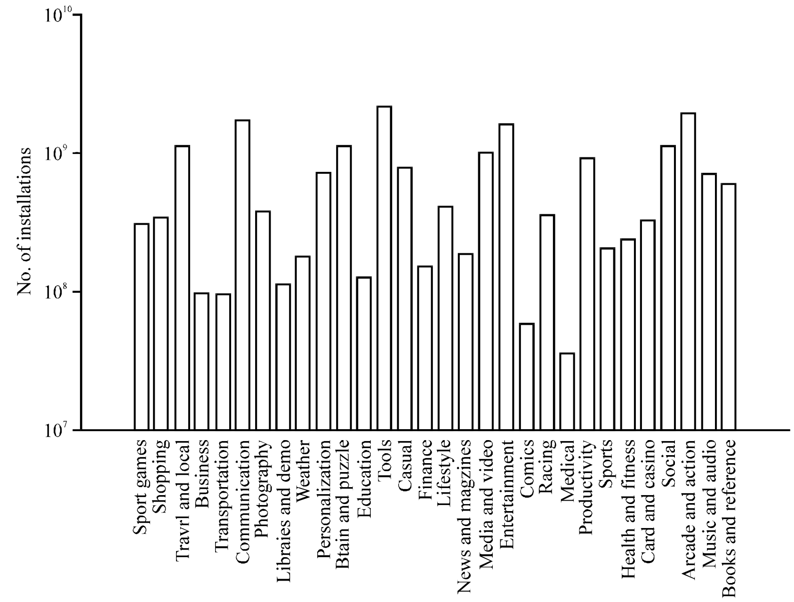

Fig. 6: Installation distribution across categories

generated (1) Tools (2) Arcade and action, (3) Communication (4) Entertainment and (5) Travel and local, as shown in Fig. 6.

Price, rating and installations: To understand the relationship among the price, rating and installations of applications, this study models a multivariate regression problem. That is, the installation of an application y_i is a variable dependent on the price x_p and the rating x_r of the application. That is:

$$Y_i = \alpha_p x_p + \alpha_r x_r + \beta \tag{2}$$

Given all the data collected, the model is denoted as:

$$Y = {}_a + \beta \tag{3}$$

where, $Y = (y_{i1}, y_{i2}, \cdots, y_{in})^T$, $A = (\alpha_p, \alpha_t)^T$, $X = (X_p, X_r)^T$, in which $X_p = (x_{p1}, x_{p2}, \cdots, x_{pn})^T$, $X_t = (x_{r1}, x_{r2}, \cdots, x_{rn})^T$ and n denotes the dimension of vectors, i.e., the number of applications.

The study extracts the values of those variables from the data set and constructs vectors for the installations, price and rating of applications with 100,000+dimensions. Then the multivariate regression model is solved using the least squares and get the coefficients as follows:

$$x_p = -4378.49,\ x_r = 41855.03,\ \beta = -85808.38.$$

The results tell that the installations of users comply with a natural law that the lower the price and the higher the rating, the more the installations.

Measurement of relationship: This section steps further to exploit the correlation between applications which are connected in terms of the properties of applications. To be specified, it investigates the assortativity in node degree and the similarity of application category, price and popularity.

Degree assortativity: Assortativity in complex network is a characteristic to identify the tendency of nodes to connect to others that are similar or different in specific ways. Although there are kinds of measurements for the similarity of nodes, researchers often examine the assortativity using the node's degree, for correlation between nodes of similar degree are often observed in many real networks.

The degree assortativity coefficient is defined according to study of Newman (2003a). That is:

$$r_d = \frac{\sum_{ij} ij(e_{ij} - q_i q_j)}{\sigma_q^2} \tag{4}$$

where, q_i denotes the distribution of the remaining degree, e_{ij} refers to the joint probability distribution of the

Table 3: Degree and property assortativity in app relationship networks

Assortativity	G_v	G_i
Degree	-0.175	-0.069
Category	0.642	0.687
Price	0.134	0.379
Rating	0.004	0.019
Installation	-0.025	0.118

remaining degrees of two nodes and where σ_q is the standard deviation of the distribution q_i. Empirical results listed in Table 3 show that the two networks of application relationship show disassortative mixing, or dissortativity, as applications with high degree tend to attach to low degree applications. That is, popular applications are not tending to connect with popular applications. This would facilitate the application discovery, which means users will not be constrained only in the circle of popular applications.

Property assortativity: The property assortativity indicates the similarity between connected applications from the view point of application properties, including the price, rating, installation and category. The definition of assortativity coefficient is defined as in study (Newman 2003b) as:

$$r_p = \frac{T_r \varepsilon - |\varepsilon|^2}{1 - |\varepsilon|^2} \tag{5}$$

where, ε is the matrix consisted of elements e_{ij}. Here, e_{ij} denotes the fraction of edges connecting a node with property i to another node with property j in the network.

It can be figured out from the results listed in Table 3 that in both app relationship networks, connections between applications mostly rely on their categories and do not correlate much with their ratings, while installations between connected applications tend to behave reversely across the two networks. That is, users may tend to view or install applications with same categories.

USER NAVIGATION NETWORK

This section studies the possible influences imposed by the android market on the navigating behaviors of mobile users. To this end, it construct a user navigation network based on the major relationship among applications on the website. Statistics and analysis in this section reveal the characteristics of the user navigation network as a complex network.

Table 4: Statistics and measurements of user navigation network

Statistics and measurement	G_u
No. of nodes	103348
No. of edges	822558
No. of mutual edges	253402
Ratio of reciprocity edges	0.308
Diameter	31
Average shortest path length	8.117

Network construction: Although, each of the alsoview and alsoinstall relationships is treated as a symmetric relationship by semantic understanding, their links on website are not all reciprocity. This section constructs the user navigation network leveraging the directed graph since web links on the webpages are directed. Since users would follow both kinds of links, it is assumed that the alsoview and alsoinstall links don't make much difference in terms of navigating users to discover applications. After all, in the user navigation network, each node denotes an application and a directed edge denotes a navigating link on the website between two applications. The size of user navigation network is identified by its number of nodes and edges, as shown in Table 4.

Statistics and analysis: This Section investigates some statistic metrics of the user navigation network. They are expected to reveal the influences imposed by the online market on the behaviors of mobile users. The empirical results and their analysis are described from both coarse-grain and fine-grain.

In-degree distribution: In the user navigation network, the out-degree of a node indicates is destined and limited by the website. Therefore this part of study focuses on how many applications will link in to each application, which is denoted as the in-degree of each node.

The scale-free in-degree distribution, as shown in Fig. 7, demonstrates that there are applications refereed by many other applications in the user navigation network, with the maximum in-degree as 491, regardless of the out-degree of each application which is limited to be less than 8. This suggests that users tend to flock to some popular applications when surfing in the app market.

Reciprocity links: The reciprocity of the network is further investigated. It measures the tendency of node pairs to form mutual connections. Any pair of applications with a reciprocity link point to each other in the market, thus user can jump forward and back between them. This kind of links facilitates the browsing convenience of users

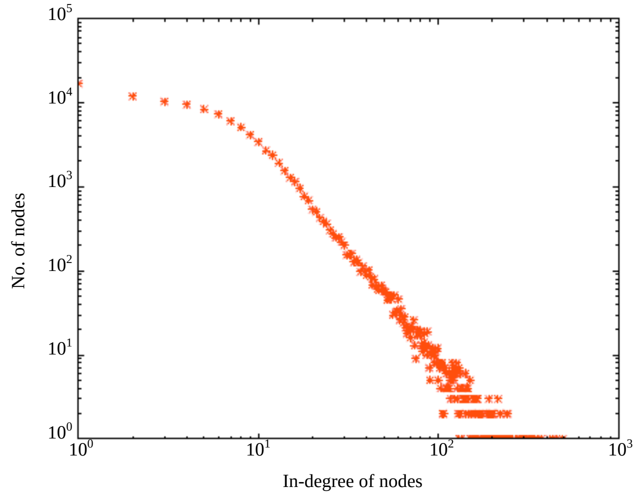

Fig. 7: In-degree distribution in user navigation network

but occupy the chances for other applications to be discovered by users. The link reciprocity is defined as the ratio of the number of links pointing in both directions $\varepsilon^{\leftrightarrow}$ to the total number of links ε:

$$r = \frac{\varepsilon^{\leftrightarrow}}{|\varepsilon|} \tag{6}$$

Table 4 shows that more that 30% of the edges are mutual ones, which is higher than the one in address book of E-mail networks (Garlaschelli and Loffredo, 2004). Therefore there is a probability of 0.308 for users to find a link to the previous application when they want to jump back but the probability of discovering a new application is only 0.692 when users follow a link.

Strongly connected components: Components in a directed graph are maximum connected sub graphs with weakly or strongly connected nodes. Nodes in strongly connected components are reachable by each other while nodes in weakly connected components are reachable by each other in the corresponding undirected graph.

Measurements related to components in the user navigation network indicate the range of the application discovery in the market. A node in a same strongly connected component can be reached from any other node which is browsing by users on an online market website. While weakly connected components that are components in the undirected conversion of the user navigation network have been studied in the app relationship networks, this study currently focus on the strongly connected components.

Figure 8 illustrates the sizes of all components and the distribution of component sizes, which shows that almost all nodes, with 103028 out of 103348 nodes, are in the largest component. It can also be found that most strongly connected components only include single node, with 157 out of 176 components. That is, most applications in the user navigation network can be reached each other, while few of them don't have bilateral paths to other applications. Thus it needs no extra search for users to reach other application from one in the market.

Average path length: The path length in the user navigation network means how many hops users need to forward before reaching an application from another one. To some extent this metric determines the efficiency of application discovery in the market.

Since not all nodes in the user navigation network are connected, the average path length is defined as the average one of all connected nodes. Numerical results listed in Table 4 tell that although the average path length 8.117 is not large, the scale of the shortest path length steps across a wide range, with the maximum length 31, which is the network diameter. That is, it is generally not long from an application to another. However, distances between some applications are not short.

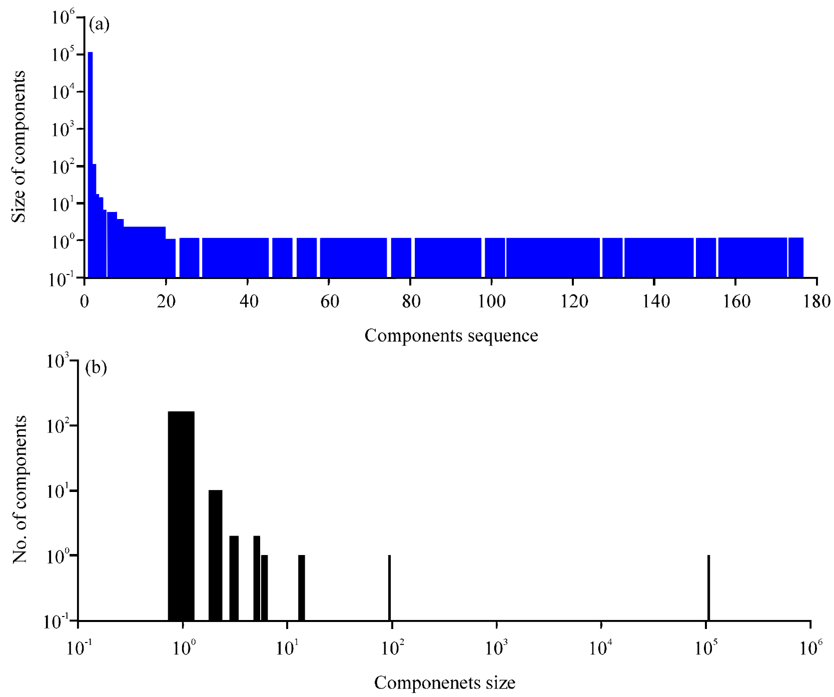

Fig. 8(a-b): (a) Size of components and (b) Distribution of component sizes

CONCLUSION

Online marketplaces of mobile applications have undergone a rapidly growth. For better understanding and utilizing it, this study takes a novel perspective to look into the android market, by leveraging the complex network view. It exploits the app relationship networks and the user navigation network from the data set crawled from Google Android Market. Based on these networks, the study measures and analyzes multilevel characteristics of them using the concepts of complex network to reveal the application relationships and the effects of application discovery. Findings of this study are original in the measurement of mobile app online markets compared to the results in the literature. They are expected to give a fundamental guidance for the better recognition, design, development and evolution of the android market. Moreover, methodologies developed by this study can be easily applied to other online markets of mobile applications.

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REFERENCES

Albert, R. and A.L. Barabasi, 2002. Statistical mechanics of complex networks. Rev. Mod. Physi., 74: 47-97.

Barabasi, A.L. and R. Albert, 1999. Emergence of scaling in random networks. J. Sci., 286: 509-512.

Blondel, V.D., J.L. Guillaume, R. Lambiotte and E. Lefebvre, 2008. Fast unfolding of communities in large networks. J. Stat. Mech. 10.1088/1742-5468/2008/10/P10008

Boccaletti, S., V. Latora, Y. Moreno, M. Chavez and D.U. Hwang, 2006. Complex networks: Structure and dynamics. Phys. Rep., 424: 175-308.

Campbell, P.R.J. and F. Ahmed, 2011. An assessment of mobile os-centric ecosystems. J. Theor. Applied Electron. Commer. Res., 6: 50-62.

Cnet, 2013. Google ties apple with 700,000 android apps. http://m.cnet.com/news/google-ties-with-700000-android-apps/57542502

Cramer, H., M. Rost, F. Bentley and D. Shamma, 2011. 2nd workshop on research in the large. Using App stores, wide distribution channels and big data in ubicomp research. Proceedings of the 13th International Conference on Ubiquitous Computing, September 17-21, 2011, ACM Press, USA., pp: 619-620.

Erdos, P. and A. Renyi, 1959. On Random Graphs I. Vol. 6, Publ. Math., Debrecen, pp: 290-297.

Erdos, P. and A. Renyi, 1960. On the Evolution of Random Graphs. Publ. Math. Inst. Hungarian Acad. Sci., Debrecen, pp: 17-61.

Erdos, P. and A. Renyi, 1961. On the strength of connectedness of a random graph. Acta Math. Hungarica, 12: 261-267.

Flory, P.J., 1941. Molecular size distribution in three dimensional polymers. I. Gelation[1]. J. Am. Chem. Soc., 63: 3083-3090.

Garlaschelli, D. and M.I. Loffredo, 2004. Patterns of link reciprocity in directed networks. Phys. Rev. Lett., Vol. 93 10.1103/PhysRevLett.93.268701

Girardello, A. and F. Michahelles, 2010. AppAware: Which mobile applications are hot? Proceedings of the 12th International Conference on Human Computer Interaction with Mobile Devices and Services, September 7-10, 2010, Lisbon, Portugal, pp: 431-434.

Girvan, M. and M.E.J. Newman, 2002. Community structure in social and biological networks. Proc. Natl. Acad. Sci. USA., 99: 7821-7826.

Henze, N. and S. Boll, 2010. Push the study to the app store: Evaluating off-screen visualizations for maps in the android market. Proceedings of the 12th International Conference on Human Computer Interaction with Mobile Devices and Services, September 7-10, 2010, Lisbon, Portugal, pp: 373-374.

Henze, N., B. Poppinga and S. Boll, 2010. Experiments in the wild: Public evaluation of off-screen visualizations in the android market. Proceedings of the 6th Nordic Conference on Human-Computer Interaction: Extending Boundaries, October 16-20, 2010, Reykjavik, Iceland, pp: 675-678.

Henze, N. and S. Boll, 2011. Release your app on Sunday eve: Finding the best time to deploy apps. Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services, August 30-September-2, 2011, Stockholm, Sweden, pp: 581-586.

Henze, N., M. Pielot, B. Poppinga, T. Schinke and S. Boll, 2011. My app is an experiment: Experience from user studies in mobile app stores. IJMHCI, 3: 71-91.

Holzer, A. and J. Ondrus, 2011a. Mobile application market: A developer's perspective. Telematics Inf., 28: 22-31.

Holzer, A. and J. Ondrus, 2011b. Mobile application market: A mobile network operator's perspective. Proceedings of the 8th Workshop on E-Business, December 15, 2009, Phoenix, AZ., USA., pp: 186-191.

Lancichinetti, A. and S. Fortunato, 2009. Community detection algorithms: A comparative analysis. Phys. Rev. E, Vol. 80 10.1103/PhysRevE.80.056117

Lim, Y., H.M. Kim, S. Kang and T.H. Kim, 2011. Recommendation algorithm of the app store by using semantic relations between apps. Proceedings of the 2nd International Conference on Ubiquitous Computing and Multimedia Applications, Volume 151, April 13-15, 2011, Daejeon, Korea, pp: 139-144.

Muller, R.M., B. Kijl and J.K.J. Martens, 2011. A comparison of inter-organizational business models of mobile app stores: There is more than open vs. closed. J. Theor. Applied Electron. Comm. Res., 6: 63-76.

Newman, M.E.J., 2003a. Mixing patterns in networks. Phys. Rev. E, Vol. 67 10.1103/PhysRevE.67.026126

Newman, M.E.J., 2003b. The structure and function of complex networks. Soc. Indust. Applied Mathe. Rev., 45: 167-256.

Rapoport, A., 1951. Nets with distance bias. Bull. Math. Biol., 13: 85-91.

Rapoport, A., 1954. Spread of information through a population with socio-structural bias: Iii. suggested experimental procedures. Bull. Math. Biol., 16: 75-81.

Rapoport, A., 1957. Contribution to the theory of random and biased nets. Bull. Math. Biol., 19: 257-277.

Rubinov, M. and O. Sporns, 2010. Complex network measures of brain connectivity: Uses and interpretations. NeuroImage, 52: 1059-1069.

Shanker, O., 2010. Complex network dimension and path counts. Theor. Comput. Sci., 411: 2454-2458.

Tuunainen, V.K., T. Tuunanen and J. Piispanen, 2011. Mobile service platforms: Comparing Nokia OVI and apple app store with the IISIn model. Proceedings of the 10th International Conference on Mobile Business, June 20-21, 2011, Como, pp: 74-83.

Watts, D.J. and S.H. Strogatz, 1998. Collective dynamics of small-world networks. Nature, 393: 440-442.

Yan, B. and G. Chen, 2011. Appjoy: Personalized mobile application discovery. Proceedings of the 9th International Conference on Mobile Systems, Applications and Services, June 28-July-1, 2011, Bethesda, MD., USA., pp: 113-126.