Communication based on unilateral preference on Twitter: Internet luring in Japan

Kimitaka Asatani[1], Yasuko Kawahata[2], Fujio Toriumi[1], and Ichiro Sakata[1]

[1] The University of Tokyo, Graduate School of Information Science and Technology, Hongo, Tokyo 113-8654, Japan asatani@gmail.com

[2] Gunma University, Aramaki-machi, Maebashi, Gunma 371-8510, Japan kawahata@si.gunma-u.ac.jp

Abstract. In this paper, we focus on unilateral preference for a group of specific kind of persons as a factor of network formation. Homophily and preferential attachment explain a large part of the formation of online social networks (OSN). Unilateral preference is also assumed to have important roles in OSNs, where high searchability exists with no geographical restriction. To observe unilateral preferences in a social network, we analyzed a user network constructed through interaction between those who make Japanese tweet(s) about "runaway" and those who react to them. In this case, a large proportion of the tweets are assumed to be made by young girls and most of the latter are adult men. By observing the user network, the network is found to have unsurprisingly bipartite structure composed of a thousand former users and several thousand latter users. In spite of a few friendship links among these users, about 19% of users in the latter group take one-to-many communication with users in the former group. Therefore, communications that assumed to be based on unilateral preference exist on a considerable scale. The proportion of reply message between users that regarded to have an intention of luring is surprisingly high(61%). Furthermore, we extract the core of communication by applying k-core network analysis. As a result, the proportion of luring in the core of the network is significantly higher than outside of the k-core network.

Keywords: Internet luring, Social network, Twitter

1 Introduction

Online social networks (OSNs) have no geometrical or temporal restriction and most OSN services also provide search and recommendation functions. Consequently, minority users can mutually connect [1]. Important information and memes[2] spread in OSNs. However, new risks arise in OSNs, including child pornography [3]. Some people use OSNs as a tool for luring[4] and such criminal activity has been reported worldwide. Last year (August - October 2017), the murderer kidnapped eight young women and one male in only two months using Twitter, 9 of them died in an apartment in Japan turned out [5]. In this case, the suspect found a girl who wants to commit suicide on Twitter. This incident had not been identified until the victim's family investigate her activity on Twitter. This suggests that there will be many risks that have not been apparent in the communication on Twitter. After this crime, tweets about "suicide (in Japanese)" have been officially prohibited by the system. However, other terms used for seeking target persons are not prohibited. Consequently, a lot of luring risks remain on Twitter. We need to explore how such severe communications are addressed on OSNs for preventing risks and for educating young people.

During the past decade, researchers specifically examined structure, growth mechanism[6] and dynamics including information diffusion[7, 8] of complex networks. Based on the results of this research, one can predict future links[9], detect communities[10] and identify important persons[11, 12] on OSNs. Preferential attachment[6] and homophily[13] are extremely important assumptions underpinning these theories. Preferential attachment is a property by which the number of links attached to a node corresponds to the number of existing links to the node. This property explains the mechanism that some famous people such as Justin Bieber becomes more famous and it results in numerous followers on Twitter. Homophily is a concept by which people who have the same attributes are likely to become friends. This mechanism explains the non-directional highly clustered network structure of a social network. In addition, some local homophily structures exist in the local area of the network. It can be measured by assortative mixing indicator[13, 14]. The recent research investigates the information dissemination function and social interaction function of OSN from network structure[15]. Other researchers reveal that people interact about a specific topic in OSN[16] and user interaction in specific interest communities[17]. Some studies reveal that the role of preference in online dating sites[18, 19]. However, unilateral preference is not as well researched as the mechanism of network formation.

In OSNs such as Twitter[2], people who have a unilateral preference for a specific kind of person can readily find targets because of the search functions and can approach them without geographical or temporal restrictions. Accordingly, a considerable amount of communication is regarded as based on unilateral preferences. For instance, a person who wants to find a researcher in some field can find and contact them easily. In this case, the Internet enhances the efficiency of our communication. However, in other cases including communication by which men lure young girls, communication efficiency is not always valuable for us. To elucidate and prevent risks on OSNs, many researchers survey risks for minors on OSNs[20–22]. Furthermore, researchers categorize crimes for children[23–25] and investigate the characteristics of criminal[26]. Child abuse is a globally recognized problem against which governments and companies have undertaken many deterrent efforts[27]. Through these studies and activities, individual cases and total risks of OSN are known from the microscopic and macroscopic viewpoints. However, how children and offenders mutually interact and the degree to which risk exists in OSN are still incompletely understood.

In this paper, we analyze the network structure and content of the communication between people who tweet "# 家出 (runaway)" and people who react to them and confirm the existence of unilateral preference in the communication. In Japan, "runaway" is used in more serious situations than the English "runaway." People, especially young students, who identify themselves as a runaway must leave their home because of the severe family matter or delinquency. Collected data show that most people who tweet "runaway" are apparently young girls. Most people who react to them are adult men. Using the collected data, we analyze the structure of a user–user networks of communications from aspects of whether the network is formed by unilateral preference. In addition, we investigate the proportion of luring risk existence in the communication. We define risky communications that include messages about inducing an opponent to communicate in private or in the real world. Moreover, we try to detect groups in which risky communications are likely to take a high probability using network analysis.

As a result, the existence of unilateral preference is inferred from the communication network on Twitter. The communication network is bipartite: about 19% of users in the latter group use one-to-many communication with the users in the former group, in spite of the few relationships among users. Accordingly, we assume that unidirectional preferences exist for them. By observing the communication contents, more than half of the tweets are related to luring in the collected data. Results demonstrate that highly active users are more likely to send luring message than others. Additionally, we propose a more efficient method to detect luring tweets that extract the communication core of a communication network extracted using k-core network analysis.

2 Methods

To observe unilateral preferences from the Twitter network, we collect tweets from hashtags related to "# 家出 (runaway)" and Replies, Mentions, and Likes of them. "家出" is a Japanese word that means to "runaway from home". The meaning of "家出" does not mean merely to take an excursion from the home but to stop residing there because of a serious family matter or delinquency.

2.1 Network analysis between users

We produce a user–user network from Reply, Like, and Mention reactions to the seed tweets, which contain one or more hashtags as defined in section 3. We also analyze the existence of friendships among network users. Before analysis, we consider what kinds of network structures are presumed to be observed. The network is presumed to have the structure resembling a bipartite graph between the users who make seed tweets and users who react to them, except for cases in which collected user networks are small communities associated with the hashtags. Actually, a bipartite graph structure of a user network does not necessarily indicate the existence of unilateral preferences. For example, considering the hashtag #happy, some people tweet this individually and their friends react to them. In such cases, the detected user network has a bipartite structure, but no unilateral preference to specific kind of person exists.

By contrast, people who have a unilateral preference for a specific kind of person do not react only to their friends: they react to unfamiliar users who appear to have specific attributes. These people can use the Twitter search function to find targets by searching for words indicating a mental condition or some other characteristic. In such cases, people who find a target would be regarded as reacting to more than one target. Accordingly, networks having the three following criteria are created through unilateral preferences.

- The majority consists of two groups of sparse internal communication links. Directed links are drawn unilaterally from one set to the other
- Few mutual friendships (follow–following) exist in the period of communication between users. This point cannot be observed completely because it is difficult to infer a friendship link creation date from the data. Through some links between reaction and target users that are created or deleted after the communication, we can observe the current link by assuming that the friendships are not changed greatly.
- Not a few users have 2 or more out-degrees (linking to the latter multiple users.)

To confirm the unilateral preference from the communication network structure based on the hypothesis presented above, we defined three indicators to assess the inter-user communication network. We can infer the existence of unilateral preference when the first indicator (asymmetry of the link A) takes a high value of almost 1, the second indicator density of mutual friendship D_{g_1,g_2} is around zero, and the third indicator (the average number of edges from user R) takes a certain large value.

[**asymmetry of the link** A] Users are grouped into a target user set $T = \{u \mid k_u^{in} > 0, k_u^{out} = 0\}$, reaction users $R = \{u \mid k_u^{in} = 0, k_u^{out} > 0\}$, and other users O. Here, k^{in} is the in-degree, and k^{out} represents the out-degree. The asymmetry index of the link is expressed below.

$$A = \frac{N(R) + N(T)}{N(R) + N(T) + N(O)} \tag{1}$$

Density of mutual friendship D_{g_1,g_2} The density of mutual friendship (follow and following) between group g_1 and g_2.

$$D(g_1, g_2) = \frac{\sum_{x \in g_1, y \in g_2} P(x, y)}{n(g_1) * n(g_2)} \tag{2}$$

The average number of edges from user R $\bar{k}_R$ is the average number of edges from user R to other users. If $\bar{k}_R$ is higher than 1, some users react to multiple users.

$$\bar{k}_R = N(E_{ij}\{i \in R\})/N(R) \tag{3}$$

2.2 Labeling luring reply

In Twitter, reactions of three types can be made to a tweet: Reply, Like, and Mention. A Like reaction is made without text and Mention does not likely to include a message to the person of the original tweet. Therefore, we recognize whether the reaction is luring or not for replies.

People who lure a target use many kinds of words for communication. Distinguishing dangerous communications and others is not easy. Consequently, we only consider whether a communication includes a message about inducing a person to communicate in private or in the real world for judging a message as luring or not. Furthermore, we did not weight the preferences by expression of words. For example, “give me a private message” or “tell me a LINE account (LINE is a widely used private communication tool in Japan)” is regarded as a message inducing someone to visit some private location. In addition to this, “come to my home located in Tokyo” or “Let’s meet now” is regarded as being a message inducing someone to do something in the real world.

Based on the rules presented above, three human annotators judge the tweet as luring or not. Tweets judged by more than two annotators as luring tweets are identified as luring tweets. Because of the large size of the dataset, we sampled 300 tweets randomly for each subset of the dataset and judged them as a luring tweet or not.

2.3 Detecting a subset of communications which includes luring reply with a high probability

For extracting a group of replies in which a high proportion of communication is luring, we propose two simple methods for detecting luring replies.

Tweets from highly active users We simply assume that tweets from a frequently reacted user R are more likely to be luring tweets than those of other users. Specifically, we collect replies from users who make k or more replies.

Tweets in the core of network In this case, we extract a group of dangerous tweets by observing communication networks. We assume that a typical communication is regarded as made in the core of the network. The core of the communication network is simply extracted using k-core[28] method. The k-core network is the largest sub-graph composed of nodes having k or more degrees. Specifically, tweets between users who belong to k-core (k) of the communication network are extracted.

3 Data

We gather tweets related to each hash (listed in Table 1) tag and all responses (Reply, Mention, Like) made from August 1, 2017, through February 20, 2018.

The acquired data consist of 24,773 “runaway”-related tweets from 2,614 people. Hashtags shown in Table1 are often used together in a tweet. The responses comprise 11,245 Likes, 5,306 Replies, and 894 Mentions from 5,307 people.

Table 1: Hashtags for collecting tweets

Hash Tag	Description	Number of tweets collected	Number of unique users
家出	Runaway from home	13,521	1,654
神待ち	“Waiting for supporter” - supporter means person who provides financial or life support	16,279	847
泊めて	Please stay at your home	7,569	992

The characteristics of the people making the collected tweets and responses differ greatly. We estimate that about 74% of the tweets about “runaway” are made by women (apparently young girls) from the gender estimation of sampled 100 users who made tweet(s) about “runaway” by the human annotators. In contrast, most people(94%) of reaction tweets were apparently made by adult men from the estimation of the human annotators. Although those who hide their personage on the net and people who use multiple accounts can be assumed, we assume for this study that such people are few.

4 Results

4.1 Structure of user–user communication networks

To elucidate communications between people who tweet related to “runaway” and users who react to them, we analyze the user–user network based on communication. The communication network comprises nodes (users) and edges (reactions). The two-dimensional histogram of out-degree and in-degree is presented in the Left figure of Fig. 1. In this figure, not many users(428 people) have one out-degree or more and one in-degree equal or more. These people are classified into the O (Other) group. Also, 913 users are classified into the T (target) group; 6,780 users are classified into the R (reaction) group. Consequently, the indicator asymmetry of the link is calculated as $A = 0.947$. Accordingly, the network has a structure resembling a bipartite graph.

To investigate how people mutually interact, we observed the degree distribution of T and R groups. The upper right of Fig. 1 shows the in-degree distribution of 913 T users. As this graph shows, many users (659 people) tweeting about “runaway” often receive approaches from multiple people. A plot of the distribution of the out-degrees of 6,780 users of the group R is presented in Fig. 1. We can observe several people (1,324 people) approaching two or more users. The proportion of people who approach multiple targets is 19%. Furthermore, $\bar{k}_R$ (the average number of edges from user R) takes a value of 1.62.

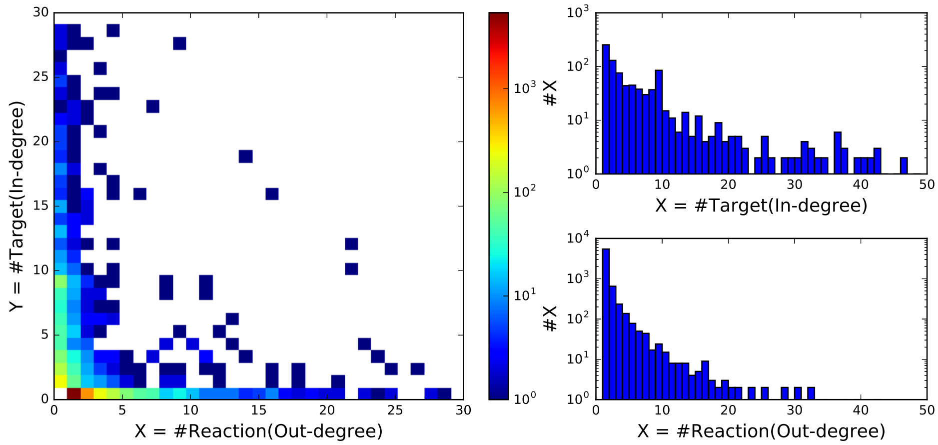

Fig. 1: **Left** Histogram of out-degrees (horizontal axis) and in-degrees (vertical axis) of the network. **Upper right** distribution of in-degrees in the set T of users. **Lower right** Distribution of out-degrees in the set R of users.

The existence of mutual friendship between users is a possible explanation for several people reacting to multiple targets. To test this hypothesis, we explore the mutual friendship between interested users by examining 3.4% of user pairs because of limitations imposed by restricted access. In Twitter, a mutual friendship is signified by mutual following. We found 106 mutual friendships from the 3.4% sampling and estimate about 3,100 mutual friendships in the total 8,121 users. The mutual friendship density D takes very low values between each community. In addition, the certain amount of unilateral following was found from R group to T groups. However, the opposite relations and mutual friendship are extremely rare between these groups. This result is obtained on the assumption that people extracted from "runaway" tweets have few mutual friendships. R users are presumed to follow T users unilaterally.

Based on analysis of the communication structure and friendship network, we can infer a unilateral preference from R users to T users because several R users react to multiple T users in spite of weak mutual friendship between them. The 19% probability that R users who react to multiple T is apparently not so large, but it seems considerably large if we consider the data collection method: collected data do not cover "runaway" communication. Moreover, the data collection period is limited. The number of T users is almost a thousand. The number of the R user is greater than a thousand if we limit them to those who react to multiple T users, which indicates that communications by unilateral preference are taken between some people. They should not be ignored. In actuality, R users search for targets in Twitter and send messages indiscriminately. They are regarded as a search for a target by the Twitter search function.

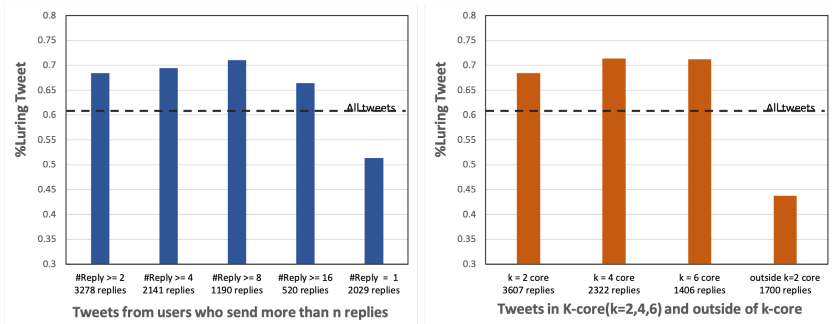

Fig. 2: **Left: The proportion of luring tweets by the number of replies.** The proportion of luring tweets from people who send x or more (far right bar) replies. The proportion in all tweets (0.610) is shown as a dotted line in this graph. **Right: The proportion of luring tweets from k-core network.** The proportion of luring tweets between people of k-core (k = 2,4,6) network and our side of k-core (k=2) network (far right bar).

From the perspective of T users, if a user tweets about “runaway,” they receive messages from users who send messages to other users who tweet “runaway.”

4.2 Detecting high-risk communications

In the detected data, we examined the proportion of luring replies (defined in section 2.2) that can engender luring to a private chat or real–world location. Here, we analyze what kinds of people are likely to lure a person who makes “runaway” tweets or whether the core of the communication network structure represents a danger of luring.

The proportion of luring tweets in all collected replies is almost 61%. This proportion is surprisingly very high. For example, the adult man replies “come to my home in Tokyo” to a girl’s tweet “I’m 17 and a high school student. I want to run away from home.” Other adult men reply simply “Please message me directly.” Non-luring Tweets are usually banter or expressions of concern from the person who tweets. However, some of these tweets might be sent in the pursuit of luring. Results show that surprisingly a large proportion of tweets about “runaway” are triggers for luring.

Highly active users To investigate what kind of person makes luring replies, we simply observe the relationship between the number of replies and the proportion of luring tweets. We first investigate the relationships between a person’s number of replies and the ratio of luring tweets. The left panel of Fig. 3 shows that the proportion of luring from people who send many replies is higher than others, which indicates that the person who is very active in this field represents a danger for luring.

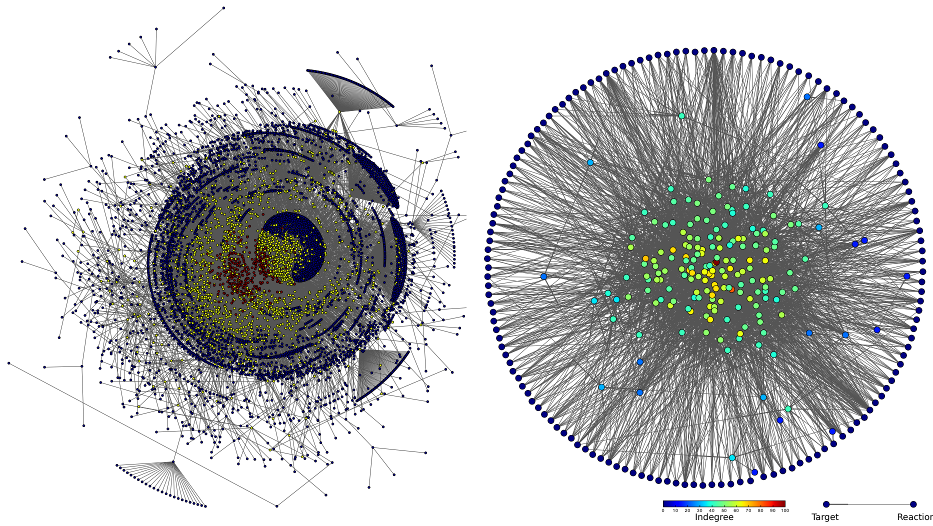

Fig. 3: **Left: The largest connected component of user network** The *k*-core part is yellow (k=2) and red (k=6). **Right: *k*-core (k=6) network of communication** A user-to-user network is based on the "runaway" tweets. Only the *k*-core part of $k = 6$ is drawn. The edge on the target node side is thick: the higher the in-degree of the node, the brighter its color.

Central core of the user network The communication network of all tweets is complex, as shown in the left panel in Fig. 3. Some local clusters created by many-to-one communication exist in the network. Almost all user on K-core networks have K incoming/outgoing links because few users have both incoming/outgoing links as shown in Fig.1. Therefore, we use K-core detection for extracting users who lure or are lured. The *k*-core part is yellow (k=2) and red (k=6) in Fig. 3. The network of K–6 is presented in Fig. 3. In this figure, the user has high in-degree in the center (they receive multiple reactions to the tweet). The user has a zero in-degree in the peripheral part. Consequently, the *k*-core (k=6) of the communication network is almost a bipartite structure. The user located in the peripheral part sends messages to multiple users in the central part. By reading the profile or tweet of each user, most of the former users are assumed to be men and most of the latter are young girls.

We investigate whether the danger communication likely to exist in the core of the network. We show the ratio of luring tweets of the *k*-core network (k=2.6) and outside the *k*-core (k=2) in the right panel of Fig. 2. The proportions of luring tweets in the *k*-core network (k=2,4,6) are equal to or higher than that of the high active user's (left panel of Fig. 2). The difference of proportion of luring between *k*-core network (k=2) and outside of the core is significantly high. This indicates that the *k*-core analysis is very for detecting dangerous communications rather than detecting users who frequently send replies. It is interesting that the proportion of luring tweets in the condition of k=4,6 is not different much. Contents of some replies from k=4,6, which is not regarded as luring, are very kind asking about the status of a girl (i.e. “are you OK?”). More detailed analysis of the contents of tweets must be conducted by reading the contents of tweets between target and reaction users. A human annotator or some NLP method must probably be applied for such analyses.

5 Discussion

By observing the conversation network related to “runaway,” we confirmed the unilateral preference from a group that consists of girls (inferred from contents and profiles) to a group that of adult men (inferred from contents and profiles) on Twitter. Friendship links and conversations inside the group were rare: there were many one-to-many links to the former group from latter group. Consequently, a person of the latter group is assumed to have unilateral preferences to the former group. Furthermore, the number of users of each set was 1,000 or more. Therefore, communications based on unilateral preference probably exist on a scale that cannot be ignored when discussing communications on a social network.

In addition to the communication structure, we observed the communication contents and asked annotators to ascertain whether communications are luring. Almost half of the communications in the extracted communications were judged to have an intention of luring. That probability is surprisingly high considering the simple method of data collection. The communication becomes even more dangerous as the user sends many replies. Moreover, the network approach, which detects the core of a communication network, more efficiently detects luring tweets than simply observing communication frequency. Almost 71% of tweets are presumed to have the intention of luring. We infer that this network approach is efficient for detecting risky communications based on other sets of hashtags.

Additionally, the existence of thousands of people who want to run away and thousands who want to invite them underscores the magnitude of invitation risk on Twitter. Among the invitations, many factors induced communication with the direct message (DM) at a frequency close to that of a person being directly called to a specific place. It is possible to set DM as OFF with the user’s authority or prohibit only DMs from people other than followers. If the invited user permits DMs from any user, then it is considered that DMs can be exchanged beyond public view. Although this DM discussion is beyond the scope of this analysis, exchanges done in that mode must be analyzed. For the present study, we detected dangerous interactions visible on Twitter, but Twitter use presents additional dangers. After the Zama incident [5] in Japan described earlier, tweets related to “suicide” have been officially prohibited by the system. However, a trend similar to that examined in this study is being observed by changing the expressions of words suggesting “suicide (in Japanese),” thereby circumventing the restrictions.

In this study, communications based on unilateral preferences were detected using a "runaway"-related hashtag as a seed. Aside from "runaway" tweets, the network contracted using "suicide" tweet is presumed to have a similar structure. However, we do not know the dangerous keywords comprehensively. Therefore, finding such unilateral preferences from the network structure is important to detect risky communications. Future studies must develop a method to discover a subset in which communications based on unilateral preference exist only from the network structure.

6 Conclusions

In this paper, we confirm the existence of unilateral preference from adult men to people who tweets about "runaway" by analysis of communication network. About 60% of tweets between them have the intention of luring. This result is important for considering and teaching risks in OSN. In the aspect of network science, we consider that unilateral preference should be taken into account as a motive of a member of the network. Further studies are needed to confirm the existence of a local structure based on unilateral preference and to analyze the impact of unilateral preferences on the global structure of the network.

References

1. Hampton, K.N.: Internet use and the concentration of disadvantage: Glocalization and the urban underclass. american behavioral scientist **53**(8) (2010) 1111–1132
2. Kwak, H., Lee, C., Park, H., Moon, S.: What is twitter, a social network or a news media? In: Proceedings of the 19th international conference on World wide web, ACM (2010) 591–600
3. O'Keeffe, G.S., Clarke-Pearson, K., et al.: The impact of social media on children, adolescents, and families. Pediatrics **127**(4) (2011) 800–804
4. Cheng, J., Danescu-Niculescu-Mizil, C., Leskovec, J.: Antisocial behavior in online discussion communities. In: ICWSM. (2015) 61–70
5. Griffiths, C.K.J.: Japanese man arrested after body parts found in cooler. CNN (2017)
6. Albert, R., Barabási, A.L.: Statistical mechanics of complex networks. Reviews of modern physics **74**(1) (2002) 47
7. Pastor-Satorras, R., Castellano, C., Van Mieghem, P., Vespignani, A.: Epidemic processes in complex networks. Reviews of modern physics **87**(3) (2015) 925
8. Guille, A., Hacid, H., Favre, C., Zighed, D.A.: Information diffusion in online social networks: A survey. ACM Sigmod Record **42**(2) (2013) 17–28
9. Wang, P., Xu, B., Wu, Y., Zhou, X.: Link prediction in social networks: the state-of-the-art. Science China Information Sciences **58**(1) (2015) 1–38
10. Xie, J., Kelley, S., Szymanski, B.K.: Overlapping community detection in networks: The state-of-the-art and comparative study. Acm computing surveys (csur) **45**(4) (2013) 43
11. Kempe, D., Kleinberg, J., Tardos, É.: Maximizing the spread of influence through a social network. In: Proceedings of the ninth ACM SIGKDD international conference on Knowledge discovery and data mining, ACM (2003) 137–146

12. Liu, Y., Tang, M., Zhou, T., Do, Y.: Core-like groups result in invalidation of identifying super-spreader by k-shell decomposition. Scientific reports **5** (2015) 9602
13. Newman, M.E.: Assortative mixing in networks. Physical review letters **89**(20) (2002) 208701
14. Lee, S.: Effect of online dating on assortative mating: Evidence from south korea. Journal of Applied Econometrics **31**(6) (2016) 1120–1139
15. Myers, S.A., Sharma, A., Gupta, P., Lin, J.: Information network or social network?: the structure of the twitter follow graph. In: Proceedings of the 23rd International Conference on World Wide Web, ACM (2014) 493–498
16. Doughty, M., Rowland, D., Lawson, S.: Who is on your sofa?: Tv audience communities and second screening social networks. In: Proceedings of the 10th European conference on Interactive tv and video, ACM (2012) 79–86
17. Beguerisse-Díaz, M., Garduno-Hernández, G., Vangelov, B., Yaliraki, S.N., Barahona, M.: Interest communities and flow roles in directed networks: the twitter network of the uk riots. Journal of The Royal Society Interface **11**(101) (2014) 20140940
18. Hitsch, G.J., Hortaçsu, A., Ariely, D.: Matching and sorting in online dating. American Economic Review **100**(1) (2010) 130–63
19. Curington, C.V., Lin, K.H., Lundquist, J.H.: Positioning multiraciality in cyberspace: Treatment of multiracial daters in an online dating website. American Sociological Review **80**(4) (2015) 764–788
20. Mascheroni, G., Ólafsson, K.: Net children go mobile: Risks and opportunities. Educatt (2014)
21. Livingstone, S., Haddon, L., Görzig, A., Ólafsson, K.: Risks and safety on the internet: the perspective of european children: full findings and policy implications from the eu kids online survey of 9-16 year olds and their parents in 25 countries. EU Kids Online (2011)
22. DeHart, e.a.: Internet sexual solicitation of children: a proposed typology of offenders based on their chats, e-mails, and social network posts. Journal of sexual aggression **23**(1) (2017) 77–89
23. Ortega, E.G., Baz, B.O.: Minors' exposure to online pornography: Prevalence, motivations, contents and effects.(la exposición de los menores a la pornografía en internet: prevalencia, motivaciones, contenidos y efectos). Anales de Psicología/Annals of Psychology **29**(2) (2013) 319–327
24. Tener, D., Wolak, J., Finkelhor, D.: A typology of offenders who use online communications to commit sex crimes against minors. Journal of Aggression, Maltreatment & Trauma **24**(3) (2015) 319–337
25. Babchishin, K.M., Hanson, R.K., VanZuylen, H.: Online child pornography offenders are different: A meta-analysis of the characteristics of online and offline sex offenders against children. Archives of sexual behavior **44**(1) (2015) 45–66
26. Magaletta, P.R., Faust, E., Bickart, W., McLearen, A.M.: Exploring clinical and personality characteristics of adult male internet-only child pornography offenders. International journal of offender therapy and comparative criminology **58**(2) (2014) 137–153
27. Steel, C.M.: Web-based child pornography: The global impact of deterrence efforts and its consumption on mobile platforms. Child abuse & neglect **44** (2015) 150–158
28. Seidman, S.B.: Network structure and minimum degree. Social networks **5**(3) (1983) 269–287