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A social network analysis of two networks: Adolescent school network and Bitcoin trader network

Victor Chang [a,*], Karl Hall [b], Qianwen Ariel Xu [b], Le Minh Thao Doan [b], Zhi Wang [c]

[a] Department of Operations and Information Management, Aston Business School, Aston University, Birmingham, UK
[b] Cybersecurity, Information Systems and AI Research Group, School of Computing, Engineering and Digital Technologies, Teesside University, Middlesbrough, UK
[c] International Business School Suzhou, Xi'an Jiaotong - Liverpool University, Suzhou, China

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ABSTRACT

This paper applies social network analysis in two experiments. In the first experiment, social network analysis is conducted on student friendship networks to find relational patterns. Then, three community detection methods are used to divide the student network. The RSiena package is used to illustrate the coevolution of friendship networks with smoking and drinking behavior. In this experiment, it was determined that in the closed network, same-sex reciprocated relationships are preferred. The second experiment analyzes a weighted trust network that involves users trading with Bitcoin on the BTC-Alpha platform. Since the dealers of Bitcoin are anonymous, there is an urgent need to record every dealer's credit history to prevent fraud and other security problems. The second experiment aims to improve security problems within the Bitcoin trust network by applying social network analysis.

1. Introduction

Social network analysis (SNA) is a research method that analyzes the relationship of a group of entities, which can be individual persons and organizations, communities, companies, countries, or other collective groups. The phenomena or data reflected by their relationship models are the focus of network analysis.

This paper applies SNA techniques to two different networks. Firstly, an adolescent friendship network, and secondly, a Bitcoin trading network. The research aims of the network analysis are to analyze how the networks are organized and to discover how networks are affected by the behavior of the individuals within them. After applying various community detection algorithms, the results are evaluated, and their advantages and disadvantages are discussed. Finally, the behavior-related effects on network evolution are analyzed by using the R package 'RSiena' [1].

Adolescents are a group worthy of being studied as adolescence is critical in the transition from childhood to maturity, involving many bodily, emotional, cognitive, and attitude changes. Social network analysis can reveal the connections between adolescents and their peers and how they affect their alcohol consumption and smoking habits [2]. Therefore, understanding these relationships can increase our understanding of how adolescent health and academic performance can be improved.

Bitcoin (B) is a cryptocurrency invented to be the intermediary for online exchange with strong cryptography technology, designed by Satoshi Nakamoto, an unknown person or group of people, in 2009. Bitcoin has quickly been popular as an investment on the market for its strong security and anonymity. According to research conducted by the University of Cambridge [3], 2.9 to 5.8 million unique users were using a cryptocurrency wallet, most of them using Bitcoin.

However, some regulators have released warning messages about adopting this innovative electronic cash. One of the reasons for this is because Bitcoin, and cryptocurrencies in general, are independent of any centralized regulatory authorities. Therefore anyone can anonymously make transactions by installing cryptocurrency client applications. Due to their anonymous nature, cryptocurrencies are often used in illegal transactions. Their high price volatility, electricity consumption, and lack of regulation are often used to criticize the use of cryptocurrencies. Therefore, the second experiment aims to analyze the Bitcoin user trust network to improve the privacy and security problems by means of SNA approaches, including centrality analysis and link analysis.

When applying SNA, identifying communities can provide information about how the network is organized. However, how to approach community detection (also known as a graph or network clustering) in the network is an unclear problem. There are no clear guidelines on how to evaluate the performance of different algorithms and how to compare them. In addition, in most social network analysis applications, the individual behaviors and attitudes of group members

* Corresponding author.
E-mail addresses: victorchang.research@gmail.com (V. Chang), drazarx3@gmail.com (K. Hall), qianwen.ariel.xu@gmail.com (Q.A. Xu), minhthaodoanle@gmail.com (L.M.T. Doan), zhi.wang14@qq.com (Z. Wang).

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and the network structure of social relationships between them are often interdependent naturally [4]. There are two important concepts related to this: homophily and assimilation. Homophily refers to the likelihood of similar people forming relationships with each other compared to dissimilar people. At the same time, assimilation refers to the phenomenon where people adapt their behavior to match their friends' behavior [5].

2. Related works

Several studies have been conducted to analyze social networks. By reviewing related literature, this paper learns about concepts related to the characteristics and analysis methods of social networks, such as homophily and assimilation in terms of characteristics, and centrality analysis, community detection in terms of analysis methods. Based on these fundamental concepts, this paper applies social network analysis to two different domains to show its usability and usefulness for decision-making.

2.1. Adolescent-related social network analysis

In [6], actor-driven models for the coevolution of networks and actor characteristics were presented. According to the joint dynamics of friendship networks research, the strength of homophily and assimilation processes is evaluated using SIENA software. They concluded that connections are typically avoided unless there exists a desirable outcome for engaging in a relationship, such as reciprocation of transitive embeddedness.

The research of [7] was conducted to map relationship profiles between teachers at a high school in Alberta, Canada, using UCINET, which is a software package for the analysis of social network data. Teachers were asked about the strength of their relationships with others, including questions about whether they socialized with other teachers outside of school hours, whether they engaged in conversations regularly, whether they would seek advice from others, or if they knew the names of the other teachers. Their analysis found that the network revolved around a small number of dominant people, which in this case were the secretary, principal, and vice-principal.

The research conducted in [8] looked at smoking behaviors within a multitude of high school friendship networks in Finland and how people within the networks were influenced by their peers. They used RSiena package to measure reciprocity, transitivity, and other metrics. They found that the smoking behaviors of ones' friends influenced their smoking behavior. Furthermore, they found non-smokers preferred to form relationships with other non-smokers and that smokers preferred to form relationships with other smokers.

Similarly, in [9], the evolution of smoking behavior in adolescent friendship networks was also explored by the same group of researchers, this time additionally accounting for parental and sibling smoking behavior across six European countries. In addition to again finding that smoking behavior is largely influenced by their connected friends, they also found that adolescents with at least one smoking parent were more likely to smoke and slightly more likely to smoke when at least one of their siblings did.

In the study by Rambaran et al. [10], the dynamic interactions between friendships and bullying relationships were investigated based on social network analysis. The authors collected a sample of 481 students from 19 primary school classrooms with equal sample sizes of males and females aged 8 to 12 years. They analyzed these samples on the basis of a relational framework and found that when two children picked on the same child, a friendship is likely to form between the two children and children are likely to bully their friends' victims. Likewise, when two children are harassed and harmed by the same bully, a friendship may form between them and children are likely to be victims of their friend's bully.

In a study also based on social network analysis, Long et al. [11, 12] placed their focus on the processes of peer marginalization, peer withdrawal and homophily associated with adolescent health status. In Long et al.'s research in 2020, they studied the relationship between anxiety disorders and disruptive behavior disorders in adolescents and adolescent friendships using social network analysis. They collected a dataset of 602 samples from four Scottish secondary schools. The study participants were all 15-year-old students. The results of their research indicate that disruptive behavior disorders are likely to be socially aggregated (e.g., homophily)and socially rewarding (e.g., peer popularity), whereas anxiety disorders do not have this tendency [11]. In the second study to investigate the connections between adolescents' chronic health conditions and their friendships with peers [12], they used a dataset of 461 samples from six small high schools in the United States. The results of the analysis were quite different from those of previous studies. Their findings suggest that the social network structure of adolescents with chronic illnesses was not significantly different from that of their peers without chronic illnesses, whereas previous studies have argued that the difference is significant.

The research by McCann et al. [13] aimed to examine the relationship between mechanisms associated with parental control, adolescent secrecy and the school environment and patterns of adolescent drinking frequency. Using a study of students aged 11 to 15, they found that teenagers had a tendency to imitate the drinking levels of their peers and that regular drinkers tended to make friends with those who had a similar drinking level to them. In addition, those who were highly controlled by their parents did not have a tendency to make friends with their less controlled peers, while teenagers who were less controlled were more inclined to make friends with each other. The tendency to befriend highly secretive peers was only found in boys' schools.

Adams et al. [14] employed longitudinal, complete friendship network data from two high schools to investigate the bidirectional association between students' healthy lifestyles and friendship networks. According to their results, lifestyles among friends are more similar than those among non-friends. This is partly because adolescents tend to be friends with people who have similar lifestyles and partly because friends also influence each other in terms of their lifestyles.

2.2. Cryptocurrency-related social network analysis

The network modeling process for cryptocurrency transaction data differs from conventional ones in that heterogeneous blockchain data from a number of sources must be processed. In Ethereum, for instance, there are two types of accounts: the contract account and the externally owned account (EOA). In addition, in Ethereum, transactional connections have a variety of meanings, including smart contract invocation, smart contract deployment, and money transfer. As a result, modeling the interactions between things in a blockchain system is a difficult task [15].

Complex network theory has been applied to model and study the cryptocurrency transaction network. For example, according to Maesa et al. [16] and Alqassem et al. [17], the Bitcoin network's size is growing faster than linearly. Moreover, the Bitcoin transaction network is getting increasingly dense and this densification adheres to the power-law rule. Javarone and Wright [18] and Ferretti and D'Angelo [19] also evaluated the "small world" phenomenon of the cryptocurrency transaction network by computing the average shortest path.

Chen et al. [20] employed the PageRank to rank the top ten nodes in the contract invocation graph (CIG), contract creation graph (CCG), and money flow graph (MFG). They discovered that financial applications are critical in cryptocurrency transaction relationships. Moreover, their research in 2020 [21] shows that there is a high frequency of transactions between the top traders in the Ethereum ERC-20 ecosystem selected by PageRank. ERC-20 is the most widely used Ethereum token standard.

Aside from the studies on cryptocurrency transaction relationships, Okorie [22] employed the network analysis of the Bitcoin and Ethereum markets to construct the Electricity-Crypto Network (ECN) system and studied the information spillover and connectedness in it.

Jiang X-J and Liu XF [23] attempted to uncover the reasons for the increase and fall of CryptoKitties as the first blockchain game by analyzing its whole history of player activities. In their study, a temporal kitten ownership transfer network was constructed. A variety of network parameters were analyzed for four phases: the priming period, the rising period, the falling period, and the serenity. According to their results, the primary reason for the game's rapid growth was the increased public attention resulting from the media. In contrast, the primary reason for the game's rapid decline was the limitations of the blockchain system, an oversupply of kittens, a decline in player revenue, as well as a widening divide between rich and poor players.

Park and Park [24] constructed the information network based on cryptocurrency websites to investigate the local and global popularity of the top cryptocurrency websites. Their results suggest that the number of top-level domains and different metrics of social network centrality is very effective in measuring cryptocurrency prices, trading volumes and market capitalization. They also identified several of the most popular cryptocurrency websites through network analysis and concluded that the production and consumption of information about cryptocurrency are centered in Europe and the Asia-Pacific region.

2.3. Research contributions

In this paper, we analyze an adolescent school network (Experiment 1) and a bitcoin trader network (Experiment 2). We define and measure the structural attributes and identify relationships within the networks. In Experiment 1, we show how these structural attributes and relationships contribute to the smoking and drinking behaviors of the adolescents within the network. Previous studies have shown a correlation between both drinking [25] and smoking [26] behavior and academic performance. Understanding the factors that influence these behaviors within school networks can provide teachers and parents with a greater understanding of their students' academic and health needs. In Experiment 2, we analyze how the roles of important individuals within the network contribute to the dynamics of cryptocurrency networks, particularly with regard to the privacy and network security.

3. Methodology

The network needs to be refined into a limited set of key performance indicators for effectively conducting analysis. These indicators are used to evaluate the structure and relationships of the networks.

3.1. Network density and reciprocity

Network density illustrates the portion of the potential connections in a network that are actual connections. The network density's value is between zero and one, where zero corresponds to a network with no relationship, and one represents a network with all possible relationships. Information in sparse networks is less likely to flow than information in dense networks [27]. Reciprocity measures the likelihood that vertices in a directed network will be linked mutually.

3.2. Network transitivity

Transitivity measures the density of loops of length three (triangles) in a network. The transitivity of the network is also called the clustering coefficient, divided into two types: global and local. The global one gives an estimate of the overall degree of agglomeration in a graph, while the local one measures the degree of agglomeration near each node in the graph [28].

3.3. Network centrality

Centrality analysis can be applied to find out the positions of nodes on the network. Compared with density, reciprocity and transitivity, which focus on the entire network or network subgroup, it analyses the individuals within the network [29]. Some analysis measures include degree centrality, betweenness centrality, and closeness centrality. Degree centrality is the most direct measure of node centrality in network analysis. The degree of a node is defined as the total number of relationships involving the node. For a directed graph, it has measures of in-degree and out-degree. Closeness centrality reflects how close a node is to other nodes in the network and betweenness centrality calculates the number of shortest paths through a point [30]. The core idea is that the interaction between two non-contiguous members depends on other network members, especially the members on the path between the two members, which have some types of control or dependence on the two non-contiguous members.

3.4. Community detection algorithms

Detecting communities may shed some light on the structure of the network and give us the chance to observe small groups by classifying the nodes with similarities [31]. However, community detection can be an unclear problem. There is no explicit definition of what objects need seeking, and there are no clear-cut guidelines on assessing and comparing the performance of different algorithms [32]. Firstly, such ambiguity leaves a lot of freedom to propose various approaches to the problem. So, it often depends on the specific research question and the network system being studied. Furthermore, this kind of blurred and muddled situation does research in this field progress slowly. It has sped up the prorogation of questionable concepts and methods [33]. In this paper, three techniques are used for community detection: the Girvan–Newman Algorithm, Label Propagation, and Fast Greedy.

3.4.1. Girvan–Newman algorithm

The premise of the Girvan–Newman algorithm is that in a network, the number of shortest paths through the edges inside the community is relatively small, while that between the communities is relatively large [34]. Based on this idea, the Girvan–Newman algorithm repeatedly calculates the shortest path of the current network, then deletes the edge with the largest betweenness [35]. Finally, the algorithm stops under certain conditions, and the community structure of the network can be obtained.

3.4.2. Label propagation

Label Propagation is a graph-based semi-supervised learning approach. Its principle is to predict the unmarked node by using label information of the marked nodes. The labels of the nodes are passed to other nodes by similarity. The more similar the nodes are, the easier it is to spread the labels [36].

3.4.3. Fast greedy

Fast Greedy is a fast community discovery algorithm based on the greedy algorithm [37]. The basic idea is to first set each vertex in the network as a separate community. Each iteration selects the two communities that produce the largest module Q to merge until the entire network merges into a community.

3.5. Rsiena

The R package 'SIENA' used is short for Simulation Investigation for Empirical Network Analysis. According to the Stochastic Actor-oriented models [38], models for repeated measures of social networks are statistically estimated. It is a tool for analyzing the network panel data, including two or more 'waves'. The model provides a means to quantify the ways how the behaviors of the actor in a dynamic social network are influenced by the network structure and behaviors and features of the ego and alters.

3.6. Edge weight prediction

The Weighted signed networks (WSNs) can be described as the networks in which edges are encoded with positive and negative weights. Therefore, they can capture many different types of social relationships between people, such as positive and negative relationships, trust and distrust, and like and dislike [39]. Kumar et al. [39] were the first to provide an algorithm to predict edge weights in WSNs. They proposed two innovative measurements of nodes' behavior in predicting the edges' weights of WSNs. The first metric is the goodness of a node, intuitively capturing the extent of trust or like of this node by other nodes. In contrast, the fairness of a node is the second metric capturing how fair the node is in rating the trust or likeability level of other nodes. The results were also generalized and much more reliable as they assessed the accuracy by implementing the method on six datasets.

4. Experiment 1: adolescent school network

4.1. Data and operationalization

The social network dataset studied in this report was collected from the Teenage Friends and Lifestyle Study [40]. The sample covers a cohort of adolescents at a secondary school in Scotland and Glasgow, including friendship network data, alcohol consumption, smoking behavior, and other lifestyle variables such as leisure activities and music taste. The information was traced over their second, third and fourth years, starting in 1995 with pupils aged 12–13 and ending in 1997. 160 pupils participated in the study, of which 129 were present for all three measurement points. Using this data, we analyzed the complete cases for simplicity and there are no obvious qualitative differences between the 129-pupil subsample and the full sample. Some questions about cannabis consumption, taste in music, geographical information and others were also asked, but this report will only focus on the part of smoking, drinking behavior and social networks.

The friendship networks were formed by friendship choice information on up to six friends. Participants were asked to write down the names of people they consider to be friends and distinguish between friends or best friends. The limitation of numbers is aimed to prevent the creation of social networks with too few connections and avoid subjects naming peers who are not close friends. In the data, the average numbers of reported friends of the three-time points are 3.48, 3.44 and 3.59 and the modes are 3, 3 and 5, respectively. In addition, only 12% of pupils named equal to the maximum number, indicating that the upper bound of the maximum number of friends might not affect the research results in this kind of degree.

For easy processing and analysis of data, the categorical values collected by the questionnaires were numerically encoded. They are shown as follows:

- Friendship: 1 represents "best friend", 2 represents "just a friend", and 0 represents "no friend".
- Tobacco consumption: 1 represents no consumption, 2 represents occasional consumption and 3 represents regular consumption (more than once per week).
- Alcohol consumption: 1 represents no consumption, 2 represents consumption once or twice per year, 3 represents consumption of once per month, 4 represents consumption of once per week and 5 represents consumption of more than once per week
- Gender: 1 represents male, 2 represents female

4.2. Network visualization

Fig. 1 shows the friendship network of pupils at the first time point. The size of the vertices is determined by the total degree, meaning that larger nodes occupy a more important position in the network. It was discovered that there exists a small and isolated group within the network.

Table 1
Network analytics overview.

	Density	Reciprocity	Transitivity
Time point 1	0.027	0.55	0.36
Time point 2	0.027	0.56	0.31
Time point 3	0.028	0.64	0.42

4.3. Descriptive node features

While visual networks are useful for high-level data inspection, one of the essential features of social network analysis is quantifying the characteristics of nodes on the network. Table 1 presents the figures for density, reciprocity, and transitivity to give an overview of the whole network.

4.3.1. Density

The density of this friendship network is approximately 2.7%. It is a sparse network with relatively few edges. This is to be expected as it is a friendship network with the limitation of naming up to six friends.

4.3.2. Reciprocity

Reciprocity reflects the fact that only half of the friends in this study have confirmed each other, so there will be such a situation where one regards the other as a friend, and the other does not think so. It was also found that this value increased slightly by around 10% in the last year's observations, showing that their friendship with each other had become stronger after two years. It might be an expandable topic in the field of praxeology or psychology but will not be discussed in-depth in this paper.

4.3.3. Transitivity

In the table, transitivity refers to global transitivity, which is calculated by disregarding direction. The changes in values indicate that the interaction between the network is getting closely related.

4.3.4. Degree centrality

As the out-degree is limited to a maximum of six, it is no need to pay attention to this measurement. By considering the in-degree of nodes, it can be found that students 044 and 058 have relatively high in-degree in the first two time points and in the fourth year (time point 3), 049 is the most important node. A person with a high in-degree of centrality is an object that other people want to associate with. It can be understood that he has a high reputation in this network, reflecting his attractiveness as a person. Therefore, these pupils may lead to the content of communication in this network circle. However, there is a noteworthy point that no one person remained as its most important member during the three years. For example, the in-degree of 044 and 058 became 5 in the last year, which is much smaller, showing the decline of their influence.

4.3.5. Closeness and betweenness centrality

As most nodes have a closeness of around 0.08, they have no difference in distance to others in the network. For betweenness centrality, the same thing happens as the degree centrality. Pupils with high betweenness centrality are not consistent for three years. Nodes 085, 100, and 123 are the three with the highest betweenness, reflecting that they were more active than others at different times.

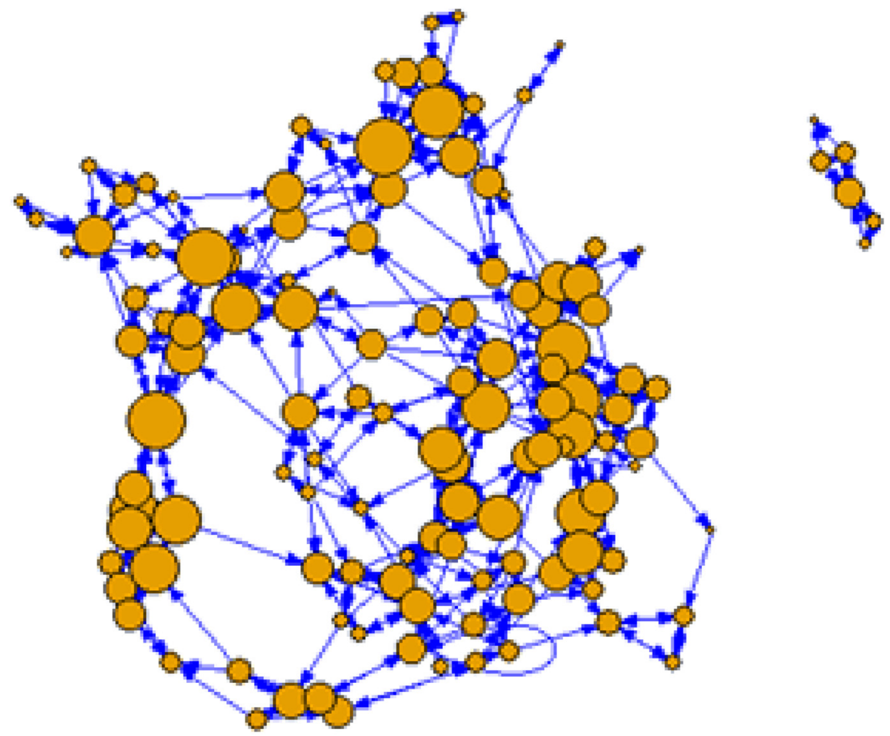

Fig. 1. Layout of the network at the first time point.

Table 2
Clique's drinking frequencies.

	Index (frequency of drinking)				
Clique 1	123 (4)	065 (3)	107 (4)	052 (5)	087 (4)
Clique 2	004 (2)	008 (2)	039 (2)	118 (2)	127 (2)

Table 3
Community analysis algorithm comparison.

	GN algorithm	Label propagation	Fast greedy
Number of communities	11	20	10
Modularity	0.765	0.715	0.771
Time complexity	$O(E^2V)$	$O(V^2 + E)$	$O(V + E)$

4.4. Community detection

In order to explore whether adolescents' smoking and drinking behaviors are related to the subgroups of students, community detection is used to discover groups in their friendship networks. In this paper, the fourth year's data will be analyzed as an example. Before starting, the network was changed to undirected by creating an undirected link between any pair of connected nodes.

As it is a sparse network, most cliques consist of around two to four people and the size of the largest clique is seven. Therefore, the cliques with the maximum number of nodes are observed carefully. The cliques contain pupils with an index of 113, 049, 050, 057, 060, 074 and 106. The frequency of their drinking is respectively 4, 4, 4, 3, 3, 4, 4 (3 for once a month, 4 for once a week). It seems that in these small subgroups with close relationships, each member has similar drinking behavior. The same correlation was observed by checking the second time point for validation.

Three algorithms are used to detect different groups in the network: the Girvan–Newman Algorithm, Label Propagation, and Fast Greedy. Fig. 2 visualizes the results of community discovery using Fast Greedy algorithms. The figures above each point represent the frequency of smoking for each person and there is some missing data. Additionally, the table below shows the results of each community discovery algorithm. It is noted from Fig. 2 that three isolated nodes, located in the top-left, are regarded as three separate communities. Thus, in Table 3, the number of communities is reduced by three. Modularity is a commonly used method to measure the strength of network community structure, which can be used to quantitatively measure the quality of network community division.

4.5. Coevolution of networks and behavior

The RSiena package is utilized using R to analyze the coevolution of the friendship network and drinking behaviors. As observed at the first time point, gender and smoking consumption are used as constant covariates and drinking behavior is regarded as a changing covariate.

After defining the data set and obtaining the basic effects object, more effects can be defined to include in the coevolution model, such as structural effects like transTrip and cycle3. It also includes sender, receiver and homophily effects of smoking, drinking and gender for friendship formation, as well as indegree, out-degree and assimilation effects for drinking. It should also be noted that the dyadic measure of similarity in actor characteristics can define the homophily and assimilation effects. After executing the code, the results for the model are shown in Table 4.

5. Experiment 2: bitcoin trust network

The dataset used in this experiment is based on a user network with the weighted trust of a Bitcoin trading platform called BTC-Alpha. On this platform, every user's credit is evaluated by using the rating from Revain, which contributes to the weighted trust of the network's users.

Using Gephi, a graph visualization was generated of the whole network (Fig. 3). In order to make the graph clearer and more straightforward, every node has been assigned to various sizes and shades of red according to each one's value of degree (Fig. 4). The darker the color, the higher value of degree a node has. The edges also have different colors according to their weight, with purple indicating the highest weight and white indicating the lowest.

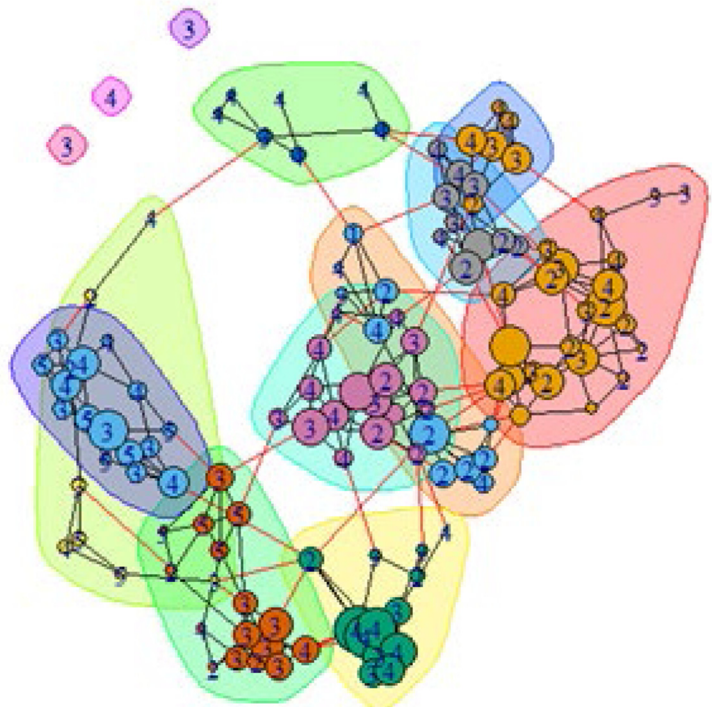

Fig. 2. Community detection using Fast Greedy.

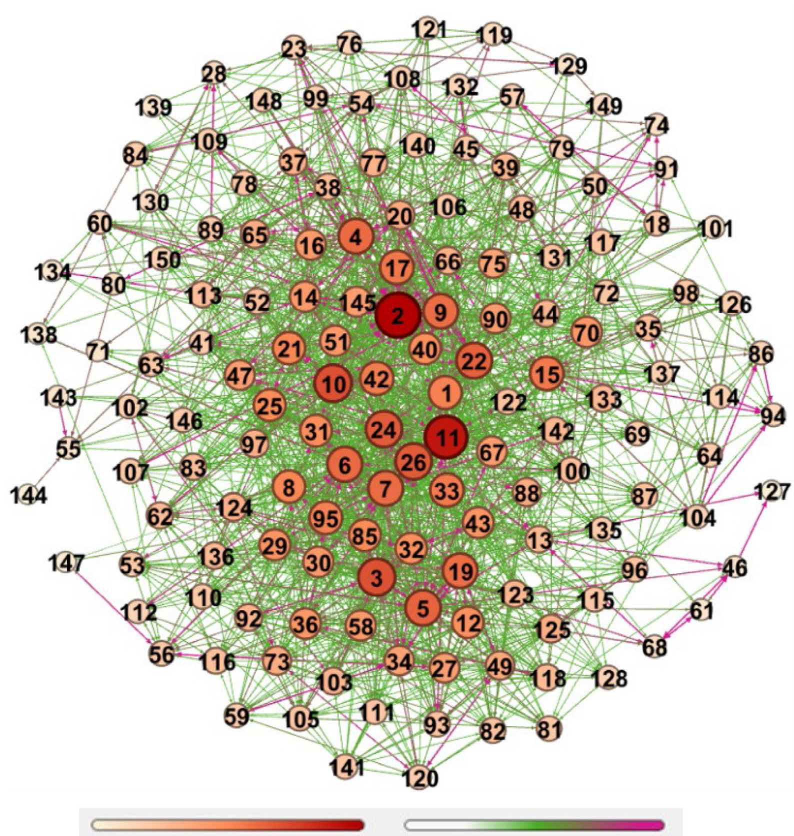

Fig. 3. Graph of the whole network.

```
> eigen_centrality(g1)
$vector
   [1] 0.498247503 0.926866271 0.754950067 0.534226028 0.677691071 0.646061239 0.711353255 0.606052688
   [9] 0.651949446 0.702864516 1.000000000 0.496129524 0.332012186 0.468756914 0.575738680 0.350776229
  [17] 0.589896213 0.158339957 0.703391821 0.407799752 0.559743894 0.697921486 0.120388462 0.773159563
  [25] 0.563150273 0.711830847 0.424652203 0.047930484 0.536243387 0.496668451 0.582600897 0.567472312
  [33] 0.591183009 0.431393954 0.210912183 0.520283770 0.326465413 0.267690158 0.319077876 0.507020957
  [41] 0.215850811 0.629260255 0.540272260 0.289875443 0.254418563 0.029613631 0.531019676 0.238464392
  [49] 0.390395959 0.125108844 0.530990438 0.295891175 0.217467851 0.159407056 0.070857515 0.201626881
  [57] 0.115725610 0.485922623 0.193112557 0.115279367 0.049644170 0.335041920 0.249159709 0.117804093
  [65] 0.363467963 0.360657950 0.479062700 0.072096772 0.206918965 0.472386409 0.075571572 0.216233484
  [73] 0.379630311 0.085684588 0.448157538 0.107687059 0.344244724 0.228300804 0.176331285 0.068972104
  [81] 0.210977391 0.268824840 0.341609190 0.100536781 0.570506581 0.092533868 0.282291172 0.435973411
  [89] 0.200488575 0.438723410 0.094746738 0.334883183 0.301241719 0.071406967 0.635934532 0.257431386
  [97] 0.366751189 0.191343732 0.150314270 0.299477586 0.086453611 0.149344548 0.346768922 0.120388329
 [105] 0.256399300 0.222932349 0.267771367 0.168956588 0.143939772 0.225766630 0.250638727 0.161809234
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 [137] 0.201950366 0.040775531 0.065329153 0.253376002 0.171523097 0.346272437 0.068021444 0.001190553
 [145] 0.498504690 0.246617334 0.021990282 0.123168253 0.065840224 0.202124107
```

Fig. 4. R code and result for computing eigenvector centrality of each node.

Table 4
Coevolution of network drinking and smoking consumption.

Network dynamics	Estimate	SE	**t-value**
Constant friendship rate (period 1)	10.862	1.023	10.62
Constant friendship rate (period 2)	8.846	0.835	10.59
Out-degree (density)	−2.953	0.068	−43.43
Reciprocity	2.218	0.106	20.92
Transitive triplets	0.616	0.045	13.69
3-cycles	−0.410	0.089	−4.61
Smoke1 alter	0.050	0.084	0.60
Smoke1 ego	0.097	0.090	1.08
Smoke1 similarity	0.467	0.158	2.96
Gender alter	−0.098	0.099	−0.99
Gender ego	0.127	0.108	1.18
Gender similarity	0.882	0.102	8.65
Drinkingbeh alter	0.049	0.071	0.69
Drinkingbeh ego	0.036	0.069	0.52
Drinkingbeh similarity	0.689	0.428	1.61
Behavior dynamics			
Rate drinkingbeh (period 1)	1.562	0.278	5.62
Rate drinkingbeh (period 2)	2.300	0.525	4.38
Drinkingbeh linear shape	0.469	0.457	1.038
Drinkingbeh quadratic shape	−0.706	0.292	−2.42
Drinkingbeh indegree	0.248	0.252	0.98
Drinkingbeh outdegree	−0.246	0.300	−0.82
Drinkingbeh average alter	1.493	0.729	2.05

Table 5
Centrality analysis results.

Centrality analysis	User ID
Highest degree	2
Highest in-degree	2
Highest out-degree	2
Lowest degree	144
Lowest in-degree	144
Lowest out-degree	41
Highest closeness	2
Lowest closeness	41

5.1. Centrality analysis

Centrality analysis is applied and divided into four types: degree centrality, closeness centrality, betweenness centrality and eigenvector centrality. The objective is to estimate how vital every given node is in the network.

5.1.1. Degree centrality

Degree centrality calculates how important a node is based on the number of edges each node has within the network and the larger the degree, the more influential the node is. The degree of centrality of the network was computed, including information about the nodes with the highest and lowest degree of centrality.

From Table 5, we can see that the user with an ID of 2 has the highest degree, in-degree, and out-degree, so the number of people who have traded with this user is the highest at 144, while user 11 also plays a significant role with a degree centrality of 132. This is also illustrated in Fig. 3, as we can see those nodes indicated in the darkest red. Furthermore, the user with the lowest degree of centrality is the user with the ID 144, with only one connection, with user 41 also only trading with one other user as a seller.

Therefore, according to degree centrality values, user 2 is the most connected user who is likely to hold most information of other users and enable them to connect with the wider network quickly.

5.1.2. Closeness centrality

Closeness centrality measures each node based on its proximity to other nodes in our network by calculating the shortest paths (pairwise geodesic distance) between all vertices. The closeness centrality of the network was computed, including information about the nodes with the highest and lowest closeness centrality.

From Table 5, we can see that a user with an ID of 2 has the highest closeness centrality, which means that this user may be the best to affect the entire network in the fastest time possible. In other words, user 2 can be a good ‘broadcaster’ within the network. Conversely, the user with the ID of 41 was found to have the lowest closeness centrality.

5.1.3. Betweenness centrality

Betweenness centrality represents which nodes have the ability to bridge gaps between nodes in a network. The betweenness centrality of the network was computed, including information about the nodes with the highest and lowest betweenness centrality.

From Table 5, we can see that the user with an ID of 2 has the highest betweenness centrality, meaning that this user is important in communication and information diffusion and has a strong ability to affect the flow within a network. Moreover, it indicates that this user may hold the authority, control the collaboration, or be located on the periphery of many clusters. Again, the user with the ID of 41 was found to have the lowest betweenness centrality.

5.1.4. Eigenvector centrality

Eigenvector centrality measures every node’s effect based on the number of links referred to by other nodes within the network. It also considers how well connected a node is and how many relationships their connections have within the network. A node with high eigenvector centrality is connected to many other nodes with high scores. The eigenvector centrality of each node was calculated and is shown in Fig. 4. We can see that the user with ID 11 has the highest eigenvector centrality at 1.0 and the user with the ID 144 has the lowest eigenvector centrality at 0.001. Both user 2 and user 11 have good scores for all-round centrality and have a strong ability to affect the entire network, instead of purely those directly connected to it.

```r
clique.community.opt <- function(graph, k){
  require(igraph)

  #####################################
  ### STEP #1: Clique discovery
  #####################################

  clq <- cliques(graph, min=k, max=k) %>% lapply(as.vector)


  #####################################
  ### STEP #2: Clique-graph creation
  #####################################

  #find edges between cliques
  edges <- c()
  for (i in 1:(length(clq)-1)) {
    for (j in (i+1):length(clq)) {
      if ( length(unique(c(clq[[i]], clq[[j]]))) == k+1 ) {
        edges[[length(edges)+1]] <- c(i,j)
      }
    }
  }

  #Create an empty graph and then adding edges
  clq.graph <- make_empty_graph(n = length(clq)) %>% add_edges(unlist(edges))
  clq.graph <- simplify(clq.graph)
  V(clq.graph)$name <- seq_len(vcount(clq.graph))


  comps <- decompose.graph(clq.graph)

  lapply(comps, function(x) {
    unique(unlist(clq[ V(x)$name ]))
  })
}
```

Fig. 5. R code for the CPM algorithm.

Table 6
Link analysis results.

Link analysis	Results
Density score	0.072552
Connectedness score	1
Isolation score	0
Authority	user 11
Hub	user 51

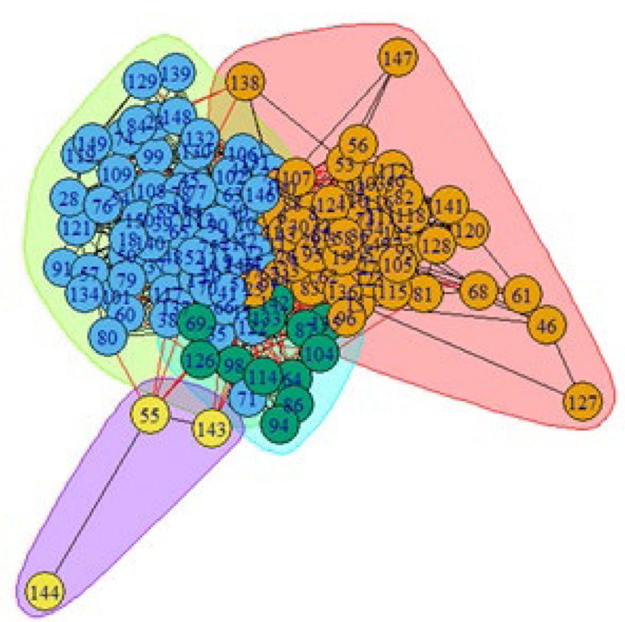

Fig. 6. Community detection graph using modularity maximization.

5.2. Link analysis

Link Analysis uses links to establish higher-order relationships among nodes. It sheds some light on our investigations by visualizing complicated links within a social network that may be hard to get the full picture of manually.

Firstly, the network density is computed as a measure of network health and effectiveness (Table 6). We found that the density of our network is 7.3%, which is not particularly dense but still somewhat connected. From this, we can determine that the network does not have a strong ability to resist link failures.

Next, the connectedness of our network was calculated, and it was found that the connectedness of the network is 1 (Table 6), indicating that this graph is fully connected, meaning that there is no isolation within the network (Table 6).

Hypertext-induced topic selection (HITS) was also employed in the link analysis, which identifies the“authority” and the “hub” in a network [41]. By applying the HITS algorithm, we can see that user 11 is the authority figure of this network and 51 is the hub (Table 6).

5.3. Community detection

5.3.1. Node-centric community detection

Node-centric community detection is a popular technique used in traditional social network analysis and detects communities with different properties of nodes. Normally, based on complete mutuality, the Clique Percolation Method (CPM) can be used to aid cliques as the core to seek overlapping communities. Firstly, the graph was converted into an undirected graph. Then, the CPM algorithm was applied to the network (Fig. 5).

5.3.2. Network-centric community detection

Network-centric community detection takes the global connections within a network into account and aims to divide nodes of a network into disconnected sets. Modularity maximization is applied to the network. Modularity measures the power of a community partition by

```
> length(cfg)
[1] 4
> modularity(cfg)
[1] 0.2469605
> membership(cfg)
113 119  54  37  10  99   4   1   2  91 121  40  31  23  44  74  45 131 145 148 109 108 139 106  84
  2   2   2   2   2   2   2   2   2   2   2   2   1   2   2   2   2   2   2   2   2   2   2   2   2
 16 138 129  21  72  42 150 100 111 149  63  50  48  33  65 140  88 130  90 102  97  57 101  35  78
  2   1   2   2   2   2   2   1   1   2   2   2   2   1   2   2   1   2   2   2   2   2   2   2   2
 28  76  77 132  89  11  75  79  39  18 117  47  17 137  26  15  66  20   6  22   9  55 135 122  98
  2   2   2   2   2   1   2   2   2   2   2   2   2   2   1   2   2   2   1   2   2   4   3   2   3
 67  14  51 146 107  24 142  38  60  70 133  69  64  83  32 110  29  52   7  25  92  43 143  13   8
  2   2   2   2   1   1   3   2   2   2   3   3   3   1   1   1   1   2   1   1   1   1   4   1   1
123  80  85  62  71 103 134 136  30 116 124  68 112  95  27  46   3  36  53  73 147  56  61 125  93
  1   2   1   1   2   1   2   1   1   1   1   1   1   1   1   1   1   1   1   1   1   1   1   1   1
 49  81 115  96  12   5  34  19  59 120 126 118 128 144  87  82 105 104  58  86 114  94 141  41 127
  1   1   1   1   1   1   1   1   1   1   3   1   1   4   3   1   1   3   1   3   3   3   1   2   1
```

Fig. 7. R code for detailed information of each node using modularity maximization.

considering the degree distribution as a measurement. The resulting graph is shown in Fig. 6 (see Fig. 7).

6. Analysis of results and discussion

6.1. Experiment 1

During the process of community detection, three methods were applied to friendship networks. When comparing these three algorithms, they each have advantages and disadvantages. Regarding the data of modularity, a fast greedy algorithm has the best quality of network community division. In addition, it has the lowest time complexity. From the results shown in Table 2, it can be determined that there is no significant evidence that community division results in similar drinking behavior as in most cliques. Their drinking behaviors vary. The same conclusion was reached when using the Girvan–Newman Algorithm. With relatively high modularity in this experiment, the Girvan–Newman Algorithm results in many cases of repeatedly calculating the shortest path, resulting in high time complexity. In this experiment, the network is small, so this shortcoming has not been exposed. Fig. 8 shows the community detection result by using the Label Propagation algorithm. This algorithm almost doubles the number of divided communities and has lower modularity when compared to Fast Greedy, but by checking the graph, it can be found that pupils in the same community have a similar frequency of alcohol consumption. In this case, this method would be the most efficient one for detecting social groups formed according to lifestyle using this data set. The advantages of the Label Propagation algorithm are simple, efficient, and fast. The results are slightly different when run multiple times, showing that each iteration's results are slightly unstable.

On the aspect of behavior-related effects on network evolution, some results can be concluded from Table 4. The network part of the model is addressed first. The estimate for out-degree is negative, indicating a tendency to avoid connections unless there are other desirable properties to the friendship, such as reciprocal, transitive relations, or a same-gender relationship. In addition, adolescents appear to prefer friends with the same smoking behavior. From the smoke1 ego and drinking behavior (drinkingbeh) ego parameters, smokers and drinkers are more active in the friendship network as they tend to name more friends. When looking at the drinking behavior part of the model, the assimilation hypothesis can be confirmed, which means that it is likely for a non-drinker with drinking friends or a drinker with non-drinking friends to change their behavior to match their friends.

6.2. Experiment 2

According to the centrality analysis, we can infer that user 2 is the most connected one who is likely to hold most information of other

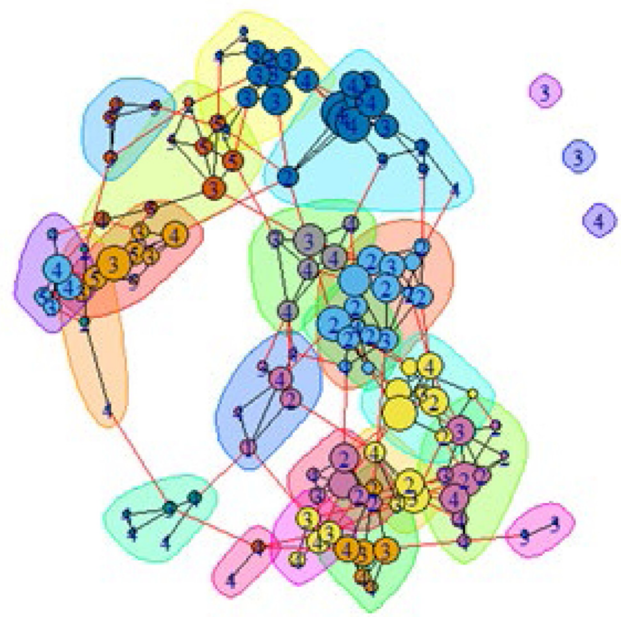

Fig. 8. Community detection using label propagation.

users and enable us to join the wider network and influence the entire network most quickly and effectively. Therefore, this user can be a good 'broadcaster' and 'bridge' when a security problem occurs in our Bitcoin user network.

As for the link analysis, it can be deduced that the Bitcoin user network is fully connected. However, the density of the graph is not very high, indicating that the network does not stay in a healthy situation to some extent. Also, it means that our network does not have a strong ability to resist link failures. If a security problem happens, the links between users should be monitored carefully in case of further loss. Moreover, with HITS's help, we also identify the authority and hub nodes (users 11 and 51, respectively) that perform well in centrality analysis metrics, so we should also pay more attention to these two users.

For the part of community detection, Fig. 6 shows that the network has four main communities where the users trade with each other more often than with those outside the community. It also indicates that they have slight strength of a community partition by considering the degree distribution as a measurement and the structure of their community is not bad according to the modularity value. When security problems threaten their interest, the power of the community should be taken seriously.

```
#find the number of friends named
f<-function(x) sum(x==1|x==2)
#funtion of getting the mode
getmode <- function(v) {
  uniqv <- unique(v)
  uniqv[which.max(tabulate(match(v, uniqv)))]
}
apply(sfriendship.1,1,f)
mean(apply(sfriendship.1,1,f))
getmode(apply(sfriendship.1,1,f))
sum(sapply(apply(sfriendship.1,1,f),function(x) sum(x==6) ))
```

Fig. A.1. R code for finding the number of friends.

```
plot.igraph(graph.1,layout=layout.fruchterman.reingold,
            edge.color="blue",edge.width=E(graph.1)$weight/2,
            edge.arrow.size=0.05,vertex.label =NA,vertex.size = deg1)
```

Fig. B.1. R code for plotting the network.

```
ungraph.3 <- as.undirected(graph.3, mode= "collapse",
                           edge.attr.comb=list(weight="sum", "ignore"))
sapply(cliques(ungraph.3), length) # clique sizes
largest_cliques(ungraph.2) # cliques with max number of nodes

#Community detection based on edge betweenness
ceb3 <- cluster_edge_betweenness(ungraph.3)
dendPlot(ceb3, mode="hclust")
plot(ceb3,ungraph.3,vertex.size = deg3)
length(ceb3)
modularity(ceb3)

#Community detection based on based on propagating labels
clp3 <- cluster_label_prop(ungraph.3)
plot(clp3, ungraph.3,vertex.size = deg3)
length(clp3)
modularity(clp3)

#Community detection based on greedy optimization of modularity
cfg3 <- cluster_fast_greedy(as.undirected(graph.3))
plot(cfg3, as.undirected(graph.3),vertex.size = deg3)
length(cfg3)
modularity(cfg3)
```

Fig. C.1. R code for community detection.

```
friendship <- sienaDependent(
  array( c( sfriendship.1, sfriendship.2, sfriendship.3 ),
         dim = c( 129, 129, 3 ) ) )
drinkingbeh <- sienaDependent( salcohol, type = "behavior" )
smoke1 <- coCovar(stobacco[,1])
gender <- coCovar(sex.F[selection129])
alcohol <- varCovar( salcohol )
mydata <- sienaDataCreate( friendship, smoke1,gender, drinkingbeh )
myeff <- getEffects( mydata )
print01Report( mydata, modelname = 'Report1' )
myeff <- includeEffects( myeff, transTrip, cycle3 )
myeff <- includeEffects( myeff,egoX, altX, simX, interaction1 = "smoke1" )
myeff <- includeEffects( myeff,egoX, altX, simX, interaction1 = "gender" )
myeff <- includeEffects(myeff, egoX, altX, simX, interaction1 = "drinkingbeh" )
myeff <- includeEffects( myeff, name = "drinkingbeh",avAlt,indeg, outdeg,
                         interaction1 = "friendship" )
myalgorithm <- sienaAlgorithmCreate(projname = 'Report1')
(ans <- siena07( myalgorithm, data = mydata, effects = myeff))
siena.table(ans, type="html")
summary(ans)
```

Fig. D.1. R code for the experiment.

```
> clp3 <- cluster_label_prop(ungraph.3)
> modularity(clp3)
[1] 0.7142992
> #Community detection based on based on propagating labels
> clp3 <- cluster_label_prop(ungraph.3)
> modularity(clp3)
[1] 0.7189024
> #Community detection based on based on propagating labels
> clp3 <- cluster_label_prop(ungraph.3)
> modularity(clp3)
[1] 0.7052805
```

Fig. E.1. R code for the results of cluster.

7. Conclusion

The results concluded in this report contribute to the literature on adolescents' relational patterns in a closed network and the association between drinking and smoking behavior within the friendship network. When considering the parameters of density, reciprocity, transitivity, and centrality, it was discovered that the network is sparse

```
> which.max(degree(g1,normalized = FALSE))
[1] 2
> which.max(degree(g1,mode="in",normalized = FALSE))
[1] 2
> which.max(degree(g1,mode="out",normalized = FALSE))
[1] 2
```

Fig. F.1. R code and results for finding the node with the highest degree centrality.

```
> which.min(degree(g1,normalized = FALSE))
[1] 144
> which.min(degree(g1,mode="in",normalized = FALSE))
[1] 144
> which.min(degree(g1,mode="out",normalized = FALSE))
[1] 41
```

Fig. F.2. R code and result for finding the node with the lowest degree.

```
> which.max(closeness(g1,normalized = FALSE))
[1] 2
> which.min(closeness(g1,normalized = FALSE))
[1] 41
```

Fig. F.3. R code and result for the nodes with the highest and lowest closeness centrality.

```
> which.max(betweenness(g1,normalized = FALSE))
[1] 2
> which.min(betweenness(g1,normalized = FALSE))
[1] 41
```

Fig. F.4. R ode and result for finding the nodes with highest and lowest betweenness centrality.

```
> gden(matrix)
[1] 0.07255234
```

Fig. G.1. R code and result for network density.

```
> connectedness(matrix)
[1] 1
```

Fig. G.2. R code and result in the density of the network.

```
> isolates(matrix)
integer(0)
```

Fig. G.3. R code and result to find the isolation score of the network.

and interaction between it is getting closely related. The important nodes are also highlighted. Three algorithms, including the Girvan–Newman Algorithm, Label Propagation and Fast Greedy, are used to detect the different communities. This paper visualizes the result of each community discovery and compares the strengths and weaknesses, concluding Label Propagation is more applicable for use in this case. It is also concluded that adolescents prefer a reciprocal relationship with the same gender. Drinkers tend to be more active in their social circle. In terms of the coevolution of the friendship network and alcohol consumption, drinkers will be influenced strongly by the drinking behavior of their friends. These findings are consistent with the findings of other studies.

Future research in this area can be conducted by including more varying covariates, such as music taste and academic performance, to investigate how other characteristics affect the formation and evolution of social networks.

Bitcoin is a kind of digital currency different from traditional currencies and it is independent of any centralized authorities. Bitcoin relies

```
#find the authority and hub
k <- 10
op <- HITS(g1,k)
op
```

```
> which.max(op[1:150])
[1] 11
> which.max(op[111:300])
[1] 51
```

Fig. G.4. R code and result for HITS analysis.

on a network where users spontaneously carry on a repeated ledger and confirm transactions involving the whole group. [42]. This system operates as a peer-to-peer network on the internet, where anyone without identifying authentication can take part by downloading the application or trading on the third-party platform. To avoid fraud and better deal with security problems, the users need to agree on opening permissions to real transaction history. Moreover, we should attach great importance to the power of the individuals and the communities using social network analysis.

Although the invention of Bitcoin is intended to protect users' privacy and prevent interference between dealers to the maximum extent, users, researchers, and even criminals have found ways to make this secure system undermined. [43] examined some of the intermediary vulnerabilities, replacing the traditional currencies and figuring out some solutions to maintain security and stability. To avoid fraud, it is essential that the users agree upon opening permissions to real transaction history [44].

By comparing the results of the community detection analysis, it can be found that the phenomena of homophily and assimilation vary in the adolescent school network and Bitcoin trading network. In the adolescent school network, both phenomena of homophily and assimilation are found as pupils in the same community have similar drinking frequencies and they have the tendency to adapt their behavior to match their friends. However, in the Bitcoin trading network, only the phenomenon of assimilation is discovered. The users in the same community trade with each other more often than with those outside the community.

This paper makes several contributions. First, the paper shows how social network analysis can be applied and analyzed in different domains for interested parties through two experiments. Second, the results of our analysis help in decision-making. For example, the analysis of the adolescent school network can provide a reference for early intervention to protect adolescent health. Furthermore, the results of our analysis of the Bitcoin trading network can help decision-makers develop measures to improve data and transaction security within the network and identify the most important links or nodes that can be targeted when security problems occur.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

See Fig. A.1.

Appendix B

See Fig. B.1.

Appendix C

See Fig. C.1.

Appendix D

See Fig. D.1.

Appendix E

See Fig. E.1.

Appendix F. Centrality analysis

See Figs. F.1–F.4.

Appendix G. Link analysis

See Figs. G.1–G.4.

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