# Inference of mobile users'social relationships using Bayesian belief network

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***Abstract*—Today, mobile phones due to the rapid growth of new technologies and the emergence of a new generation of smart phones have become more than a communication tool that not only resolves the user's communication needs, but also provide them, services for many applications. List of mobile phone subscribers include slow-level simple concepts such as time and place of calls, talk time, etc. The analysis of these low-level concepts and their influences on each other can lead to identification of higher-level concepts such as user social relationships, feelings as well as many other concepts that are not recorded in the list. Data mining process as a powerful knowledge management techniques, by exploring the history list from the interaction of mobile subscribers, which represents intentions and actual behavior of each of them, as well as behavioral characteristics of each one can provide approaches and policies for social network analysis of mobile phone subscribers and ultimately brought intelligent semantic services by deduction and finally adaptation of behavioral and social implications. In this paper, due to uncertainty in the mobile sensors, Bayesian networks have been used to identify the relations of friendship between mobile users. In addition, tried to have a special look at each person and important parameters for creation of Bayesian network to be set independently according to each person's behavioral characteristics and behavioral similarities between the two individuals for every call. The results show that the proposed method has higher accuracy (0.80) than previous methods. After calculating, the probabilities of friends believe based on social network friendship that its analysis can play an important role in identifying influential actors in social networks. Therefore, the proposed framework due to focus on mobile social networks could be used in the real world.**

**Keywords**: Mobile, friendship inference, Bayesian Networks, social network

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## I. Introduction

Recently, smart mobile phones with advanced technologies such as MMS, GPS, etc. have entered the market. These unique features and availability of these functionalities in each location and time, provides appropriate context to introduce smart services. Model of social networks is combined with mobile Internet and communications services and mobile applications [1] and users can easily via your mobile update their Facebook status, e-mail and Twitter and benefit from many other services. In this regard, many Internet-based social networks have focused lately on the phones and [2] have presented a special edition of mobile phones. The new generation of mobile applications called context aware applications are rapidly growing; these applications and services are offered based on the needs and preferences of users.

In general, it can be said that mobile communications, especially mobile environments provide large amounts of communication information and consumer behavior. Identifying consumer behavior patterns in the environment, investigating and understanding their behavior is very important and can lead to valuable conclusions. [3]

As mentioned above, the mobile phone because of its inherent characteristics and user interactions includes significant information about behavior and condition of user that indicates the potential to pursuit key concepts in the list of records, which can a small part of it can include enormous volume of communication.

In Mobile phone communities, a key issue is providing useful and helpful data in every place and time. The information contained in the records list is useful information that using them we can provide intelligent and valuable personal and social services that to suits users. Log list of mobile phones usually include contacts, messages, information and time and place data that represents a simple concept and this low-level data can be used to conclude high-level concepts such as social relations information with your that simply are not available.

Identifying the relationship of people and depth of this relationship by exploring their interactions with mobile phone could offer to provide services such as intelligent call, friendship suggestions, and social networks. In addition, introduction of important arteries of information on these networks plays an important role. As mentioned above, the analysis of the data on the user's mobile phone log list as well as some behavioral characteristics, using data-mining techniques led to the discovery of relationships such as friendship, which will lead to the creation of the social network of mobile users. In fact, as you can see in Table I with the lower-level concepts like talk time, call time, call direction we aim to find and identify the relations of friendship between the caller and the callee as well.

TABLE I. INFERENCE OF CALLER AND THE CALLEE RELATIONSHIP

| **Caller ID** | **Callee ID** | **Call duration** | **Call time** | **Call direction** | **...** | **Relationship type** |
|---|---|---|---|---|---|---|
| P4 | P92 | short | private | coming | | ... |
| P8 | P12 | average | public | outgoing | | ... |

To identify relationships between individuals, social networks of this relationship is formed that can be displayed in graph format. In this graph, nodes are people on social networks And edges Indicates a connection between people. Because of the friendship between the people on social networks are not the same, the graph corresponds to the network, can be a weighted graph where the weight of each edge corresponds to the strength and intensity of friendship.

In this study, to infer relationships between people using the identification and allocation of maximum parameters of social relations, Bayesian networks have been established and then using beleif inference algorithms, the relationship between both the individual is determined; then social network based on relationship is created And based on betweenness criteria and Closeness criteria each user was rated in the network. Finally users with the highest rate were introduce as a major arteries of information.

Related tasks of inference of high-level concepts in the field of mobile phone such as emotion, social relationships, user activity and due to the emergence of a new generation of applications called Context Aware Application in order to provide essential services is very important and a lot of research has done in this area. In following, we will mention some of them. Now mobile-based social networking has grown more than computer-based social networks. It is expected they get an inseparable part of human life, and many social interactions take place via these networks. Development and growth of these networks is required to detect social relationships between users that can lead to better service delivery to the users. Therefore, methods of inference and characterization of this relationship are of utmost importance.

## II. RELATED LITERATURE

Several articles in the field of social relations inference via mobile users were done that each has explored types of mobile phone users and their social relations.

In 2009, Mr. Jung in article [4] focused on the concepts of social dependence and a social network ontology was used to identify the secret ties between users. In this article, he has assumed that personal concepts rely on others concepts that if and only if he is socially connected to them. This article based on adaptation of the concepts in the ontology, aimed to explore social relationships.

In 2011, Mr. Min and Chu in Article [2] with Bayesian networks discovered social relations, and variables such as contact time, contact frequency, contact span, , related activities and the similarity of name, have been used to identify and inference social implications .

Bayesian network provided by them is designed with the knowledge of specialists and relying on their knowledge of a potential relationship. In 2008 in article [5],they have presented the first Bayesian network for inference of social relations in order to introduce a proposing contact system.

In 2011, Mr. Park and Cho in article [6] proposed another Bayesian network to inference personal relationships such as friendship, friend, acquaintance and working relationships. Variables such as related contacts, social activities, frequency of contact, closeness of location, etc. were identified as factors affecting the private and business relations.

In 2011, Mr. Kim and his colleague [7] developed a mathematical model to identify relationships. To design this model, characteristic of social interactions through the mobile phone were reviewed and several important parameters such as influence, cohesiveness, continuity and interaction were extracted and using these characteristics one that measured close relationship between mobile users was presented.

In the case of inference of other concepts in the context of mobile using Bayesian networks have other works were done, including Min and Lee article [8] in 2013. Also in 2014, Chu and his colleague in paper [9] used Bayesian hierarchical structure to derive user activities.

## III. THE PROPOSED METHOD

As we know, people with similar and common behavioral and emotional characteristics, have more communication with each other. In the context of mobile communications, the caller and callee are two main elements that identifying and extracting their sincerity and friendship with regard to the amount and kind of their relation and their emotional and behavioral characteristics is possible. The proposed method in this study uses two individual behavioral similarities with the individual characteristics at each communication, and attempts to provide a Bayesian network based on real data, to improve evaluation criteria for identification of social relationships.

Fig.1 presents the structure of the proposed method for identifying the relations of friendship and ultimately creating social networks provided by it. As shown in the figure to achieve the main goal there are three main steps as follows.

- Preparation of data collection and pre-processing
- Bayesian networking to inference friendship
- Social networking

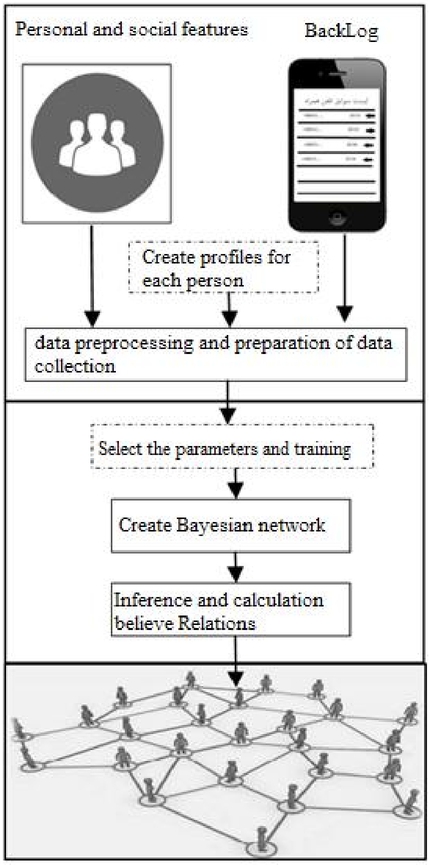


Figure.1. the overall structure of the proposed system

## A. *Preparation of data collection*

In this step, activities necessary to prepare the data for providingas training data were used to build a Bayesian network. Training data used to build a Bayesian network must have certain characteristics that most important feature is discreetness of values. Actions taken to prepare data includes the followings:

- Identification and extraction of factors
- Valuing the factors set
- Create profiles for each individual
- Data preprocessing

Performance of model depends on the parameters used to derive the friendship. Therefore, what features selected and used, is important. For this purpose, the most relevant characteristics were identified and selected. In addition to characteristics related to the relationship between two individuals, individual attributes and behavior can affect a recognition of friendship between the two. People with common behavioral characteristics and the same interests and close communication and relationships tend to be more friendly with each other. After studies and data analysis, characteristics affecting the relations of friendship were identified, including twenty features.

Contact characteristics (type of call) call direction , call duration to the caller, caller call time, callee call time (individual characteristics) job, teammate, the organization of work, the type of operator used, mobile type, neighborhood condition and behavioral characteristics (places of interest, applications used, feelings to business community, interest in travel, the forgetfulness, checking battery status, attention to the health, interest in connection with the new person and the status of business reports) are among the selected properties.

The value of individual factors, such as the being partner, teammate, etc. and other features of this type include only two statues of caller and calleeor weather they have the same personal characteristics or not, for example, calls between two partners or non-partners. Therefore, this type of features have only two statues.

Behavioral factors include hierarchical fuzzy values. For example, the values of the feeling of the working population consists feeling a little close, somewhat close and very close.

a little close < somewhat close < very close

or the values of the state of forgetfulness in reporting are never, rarely, occasionally and often.

never < rarely < occasionally < often

To set the similarities between the caller and the callee on these factors, the fuzzy rules and fuzzy inference engine is used.

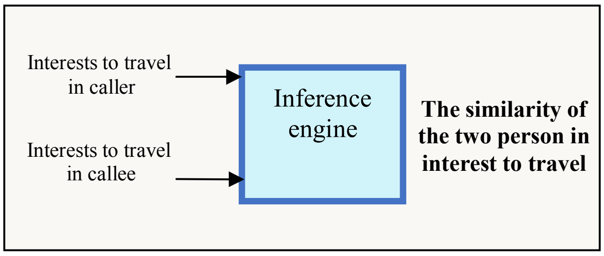


Figure.2. inference engine of behavioral factors

Values for similarity situation obtained in any of these factors between the two men are complete similarity, almost similar a little similar and non-similar. An example of fuzzy rules used to set the variables as shown below.

The proposed model is based on the characteristics of each individual for example, 10 minutes of talk time for one person may be normal or even a short time, while it may be long time for someone else, or contact hours for each person is considered according to that persons working hours. Profile created for each person in addition to the individual characteristics includes the average talk time, average length of SMS, the minimum and maximum length of calls, number of missed calls. The profiles and parameters are used in data processing as well as social network analysis.

The data used include data collected in the list of mobile phone log of individuals as well as data on personal characteristics and behavioral similarities. As mentioned, the model works on only with discrete data. Therefore, to solve the problems with continuous data, you first need to change continuous data to discrete data [12]. To use this continuous variables in Bayesian network model discretization process should be done for continuous variables.

In this study, fuzzy discretization was used .For example, for discretization of duration of the call phase diagram shown in Fig.3 is used.

It should be noted that fuzzy membership function is set based on the values of the profile created for each person separately.

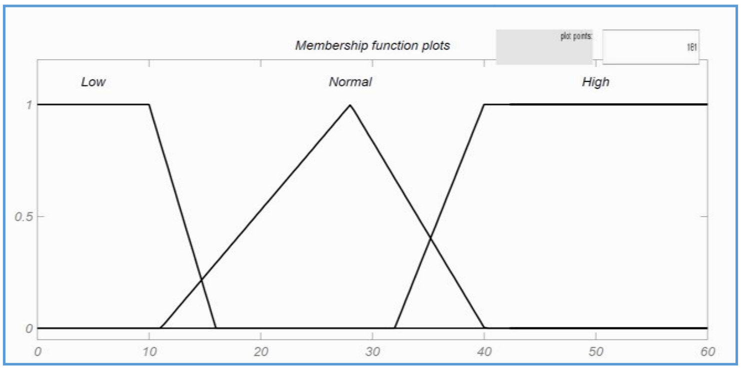


Figure.3. membership functions for parameter of talk time

The membership function is shown for a minimum of 12 minutes of talk time with an average of 22 minutes and a maximum duration of 42 minutes.

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### *B. Bayesian network to inference friendship*

Generally, variables intended to create Bayesian network with their values are shown in Table II.

After preparation and pre-processing data, data are selected according to the criteria provided. Bayesian network is created by GenIe software [11]. To build a Bayesian network algorithms such as PC [12], Greedy Thick Thinning [13] and Tree Augmented Naive Bayes [14] have been used. Models presented in the form include twenty nodes as an indicator of impact and a node as a target node.

To inference network Separate algorithms like AisSampling, EpisSampling, Likelihood Sampling, Lauritzen , BackSampling and SelfImportance [15][16] are used. In general, on Bayesian networks as the amount of data we input is high the will show the results with more likelihood.

TABLE II. SELECTED VARIABLES AND THEIR VALUES TO CREATE BAYESIAN NETWORK

| No | Variable | Value |
|---|---|---|
| 1 | Contact type | Voice, SMS |
| 2 | Contact time | Short, normal and long |
| 3 | contact time for receiver | Public, private |
| 4 | contact time for receptor | Public, private |
| 5 | Contact direction | input Output |
| 6 | Having the same job | Yes No |
| 7 | Being teammate | Yes No |
| 8 | Having the same work organization | Yes No |
| 9 | operator | Yes No |
| 10 | The same type of mobile phone | Yes No |
| 11 | Neighborhood | Yes No |
| 12 | places of interest | Categories commonalities (4) |
| 13 | Application programs | Categories commonalities (10) |
| 14 | Feeling to the business community | Quite similar, somewhat similar, slightly similar and dissimilar |
| 15 | Interest in Trip | Quite similar, somewhat similar, slightly similar and dissimilar |
| 16 | The forgetfulness | Quite similar, somewhat similar, slightly similar and dissimilar |
| 17 | Checking battery status | Quite similar, somewhat similar, slightly similar and dissimilar |
| 18 | Paying attention to the Health | Quite similar, somewhat similar, slightly similar and dissimilar |
| 19 | Interest in connection with the new person | Quite similar, somewhat similar, slightly similar and dissimilar |
| 20 | Business status report | Quite similar, somewhat similar, slightly similar and dissimilar |
| 21 | Friendship statues | Friend and not friend |

Since beleif calculate lots experimental data in GenIe is difficult or sometimes impossible, JSMILE under the Java platform libraries were used to calculations.

**Inference algorithm to calculate friendship belief**

**Input: experimental data sets**

**Output: calculation of friendship belief**

1.Setting type of algorithm based on the Library JSMILE calculation

2. Recording the number of test records

3. Choosing a random record of test data

4. Recording of valid values as observed values

5. Calculating and recording friendship belief in the selected item

6. If you percent of a friendship is more than 50% Then

7. The resulting situation is friendship

8. Otherwise,

9. The resulting situation is not friendship

10. If the number is equal to the number of records of tests then

11. Refer to 14

12. Otherwise,

13. Refer to 3

14. End

### C. Social networking

Calculating Inference for the relationship between people to all the calls and their relationship, a weighted graph that represents a social network of social relationships between individuals is created. The edges of this graph, based on the friendship belief between the caller and the callee were weighted and a weighted social network of these relationships have been established.

To create a network Node XL software [17] was used and the weight assigned to each edge, with the best results and the most efficient algorithm to calculate Bayesian network based on evaluation results, have been set. Since the probability of zero correlation between the two presents the lack of communication in this network all the edges with zero weight have been removed.

## IV. EVALUATING THE PROPOSED SYSTEM

### A. Assessment Parameters

For model evaluation recall, precision, F1 and accuracy criteria have been used.

Recall: The percentage of cases with positive labels (friend) that are predicted as positive. The criteria is calculated with (1).

Precision: percentage of positive predictions, which are correct. These criteria is calculated with (2).

F1 Criteria: The criteria uses accuracy and recalling criteria and is calculated using equation (3).

Accuracy: percentage of correct predictions that are true, this is calculated with (4).

$$\mathrm{R} = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FN})} \qquad (1)$$

$$P = \frac{\mathrm{TP}}{(\mathrm{TP} + \mathrm{FP})} \qquad (2)$$

$$F1 = \frac{2\mathrm{RP}}{(R + P)} \qquad (3)$$

$$A = \frac{\mathrm{TP} + \mathrm{TN}}{(\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN})} \qquad (4)$$

Where TP[1], is people who are friends and the proposed network presents them as friend, and FP[2], is people who are friends and proposed network would not introduce them as friend, TN[3] is people who are not friend and proposed network would not introduce them as friend, and FN[4] is people who are not friend and network introduce them as friend.

The main objective of this research was to improve the accuracy of inference, but in addition a brief qualitative assessment also was conducted on Bayesian model.

### B. Database

Data sets used in this study is MIT[5] data collection. MIT, are search institute in Cambridge, Massachusetts, has begun its activity since 2004. The data included in this collection include 94 persons active interaction) students, staff and researchers. To collect the data, Nokia 6622 under its Symbian software is used which automatically and permanently was running on their phones.

This dataset contains personal information about the people involved, such as jobs, working hours, working groups, etc. (location information via cell ID of operator, the details of voice calls and SMS) time, call duration, etc. (as well as information on Bluetooth connections). The size of this data set is about 54 MB and is provided in MATLAB.

Because Bayesian network needs complete data, so the only database of records with valid values that have the full data set only include 5987 records. The number of friend interacts is 4001 and 1987 records is for non-friends. With regard to this issue and in existence of some incomplete records as can be seen in Table III, the two data sets were selected for analysis. In the first set (D1) test data, have been chosen among incomplete data, but in the set (D2) test data were selected from the complete data.

TABLE III. PROFILE OF USED DATA SET

| Profile of Data Set | Training Set | Number Of Friends in Training Set | Number Of non-Friends in Training Set | Test Set |
|---|---|---|---|---|
| D1 | **3000** | **1987** | **4001** | **5987** |
| D2 | **598** | **1632** | **3766** | **5398** |

### C. Operating system

Assessment tests and results were done on a system with the following hardware: main memory 2 GB, a terabyte hard disk and CPU Intel (R) Core (TM) i7 2.4GHz . In addition, the

[1] True Positive(TP)
[2] False Positive(FP)
[3] True Negative(TN)
[4] False Negative (FN)
[5] Massachusetts Institute of Technology

code was in Java [Eclipse] environment [18]. The NodeXL software was used for visualizing social networks.

*D. Assessment results*

According to Bayesian networks created with multiple algorithms, the results of inferences carried out with different algorithms on each data set is shown in the following tables. Given that according to number of networks created, only some of the measures, which have presented parameters that are more acceptable, were mentioned.

In Fig.4 Networks created with K2 are shown with Greedy Thick Thinning methodology .In Tables IV and V evaluations carried out on the network (D1 and D2)were presented on two sets of data.

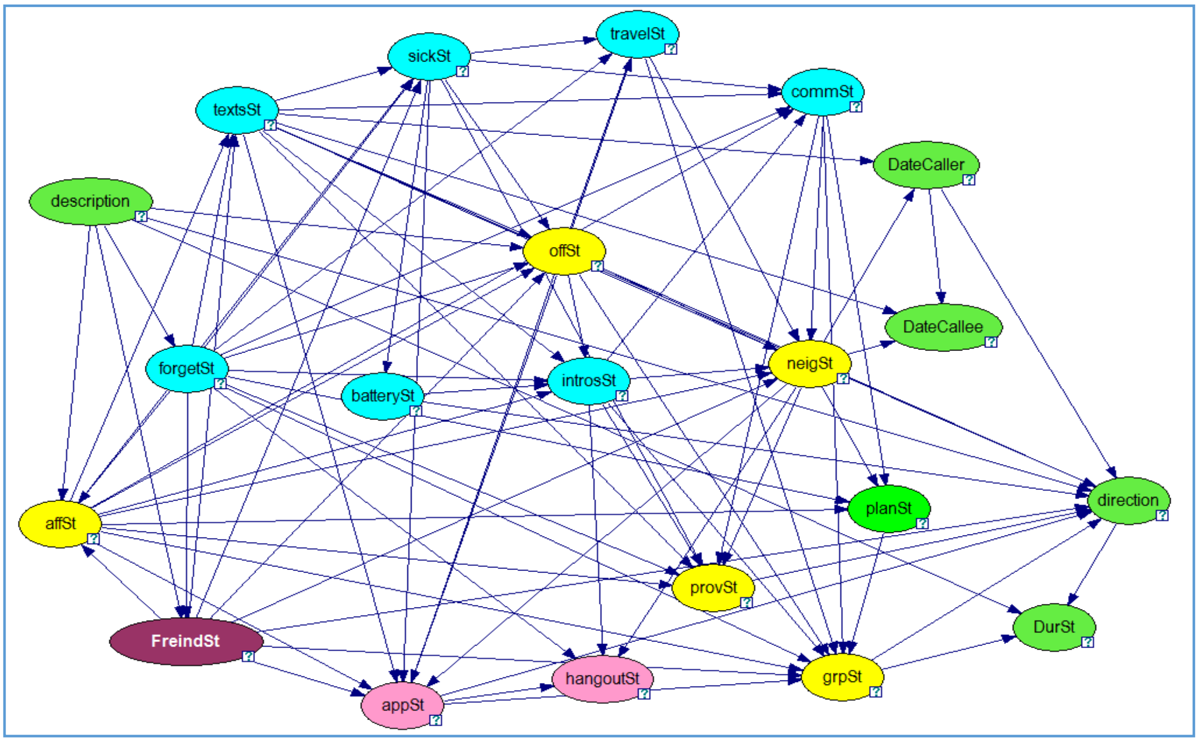


Figure 4 Bayesian network created by the GTT-K

TABLE IV. NETWORK ASSESSMENT RESULTS WITH GTT_K ON D1 DATA SET

| Belife Alghorithm | TP | TN | FP | FN | A | R | P | F1 |
|---|---|---|---|---|---|---|---|---|
| AisSampling | 1615 | 754 | 431 | 200 | 0.7896 | 0.8898 | 0.7893 | 0.8365 |
| EpisSampling | 1665 | 749 | 389 | 197 | 0.8046 | 0.8941 | 0.8106 | 0.8503 |
| BackSampling | 1602 | 765 | 416 | 217 | 0.789 | 0.8807 | 0.7938 | 0.8350 |
| Lauritzen | 1582 | 802 | 414 | 202 | 0.7946 | 0.8867 | 0.7925 | 0.8370 |
| Lsampling | 1566 | 817 | 420 | 197 | 0.7943 | 0.8882 | 0.7885 | 0.8354 |
| SelfImportance | 1666 | 752 | 335 | 247 | 0.806 | 0.8708 | 0.8325 | 0.8513 |

TABLE V. NETWORK ASSESSMENT RESULTS WITH GTT_K ON D2 DATA SET

| BelifeAlghorithm | TP | TN | FP | FN | A | R | P | F1 |
|---|---|---|---|---|---|---|---|---|
| AisSampling | 317 | 148 | 106 | 27 | 0.7775 | 0.9215 | 0.7494 | 0.8265 |
| EpisSampling | 321 | 151 | 105 | 21 | 0.7892 | 0.9385 | 0.7535 | 0.8359 |
| BackSampling | 316 | 146 | 117 | 19 | 0.7725 | 0.9432 | 0.7297 | 0.8229 |
| Lauritzen | 328 | 144 | 105 | 21 | 0.7892 | 0.9398 | 0.7575 | 0.8388 |
| Lsampling | 331 | 143 | 101 | 23 | 0.7926 | 0.9350 | 0.7662 | 0.8422 |
| SelfImportance | 328 | 148 | 104 | 18 | 0.7959 | 0.9479 | 0.7592 | 0.8431 |

Another example of surveys carried out with impressive results are Tree Augmented Naive-Bayes algorithm shown on in Fig.5.The network assessment results are shown in Tables VI and VII on two datasets of D1 and D2.

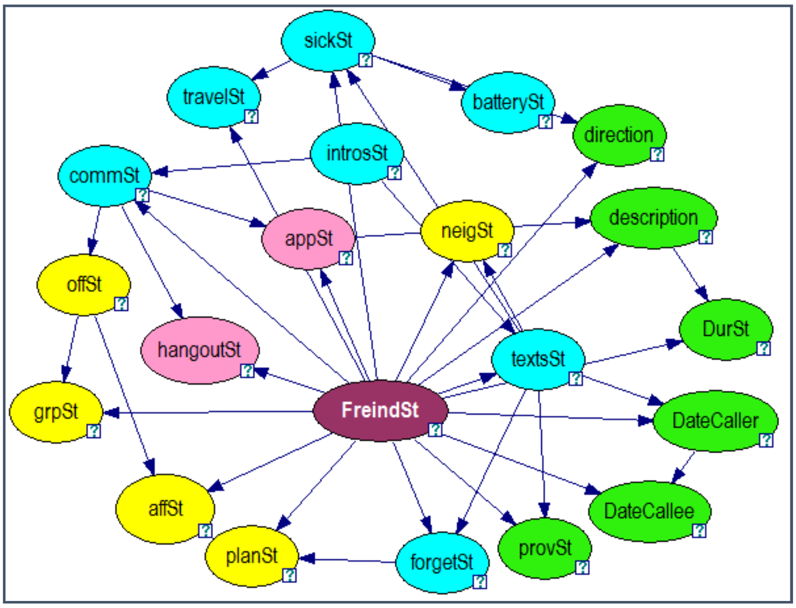


FIGURE 5. BAYESIAN NETWORK CREATED WITH THE TREE AUGMENTED NAIVE BAYES

TABLE VI. THE RESULTS OF NETWORK CREATED BY TAN ON D1

| Belife Alghorithm | TP | TN | FP | FN | A | R | P | F1 |
|---|---|---|---|---|---|---|---|---|
| AisSampling | 1541 | 832 | 468 | 159 | 0.791 | 0.9064 | 0.7670 | 0.8309 |
| EpisSampling | 1561 | 817 | 462 | 160 | 0.7926 | 0.9070 | 0.7716 | 0.7716 |
| BackSampling | 1542 | 846 | 441 | 171 | 0.796 | 0.9001 | 0.7776 | 0.8344 |
| Lauritzen | 1522 | 826 | 455 | 197 | 0.7826 | 0.8853 | 0.7698 | 0.8235 |
| Lsampling | 1494 | 858 | 470 | 178 | 0.784 | 0.8935 | 0.7606 | 0.8217 |
| SelfImportance | 1599 | 831 | 377 | 193 | 0.81 | 0.8922 | 0.8092 | 0.8487 |

TABLE VII. THE RESULTS OF NETWORK CREATED BY TAN ON D2

| Belife Alghorithm | TP | TN | FP | FN | A | R | P | F1 |
|---|---|---|---|---|---|---|---|---|
| AisSampling | 311 | 160 | 98 | 29 | 0.7876 | 0.9147 | 0.7603 | 0.8304 |
| EpisSampling | 325 | 159 | 88 | 26 | 0.8093 | 0.9259 | 0.7869 | 0.8507 |
| BackSampling | 303 | 174 | 103 | 18 | 0.7976 | 0.9439 | 0.7463 | 0.8335 |
| Lauritzen | 331 | 143 | 102 | 22 | 0.7926 | 0.9376 | 0.7644 | 0.8422 |
| Lsampling | 338 | 140 | 97 | 23 | 0.7993 | 0.9362 | 0.7770 | 0.8492 |
| SelfImportance | 322 | 158 | 102 | 16 | 0.8026 | 0.9526 | 0.7594 | 0.8451 |

Comparing results of the proposed method with mathematical models is shown in Table VIII It should be mentioned that in the mathematical model (identical conditions and experimental data D1 has been implemented.

TABLE VIII. THE RESULTS OF THE EVALUATION FOR PROPOSED MODEL AND THE MATHEMATICAL MODEL

| | TP | TN | FP | FN | A | R | P | F1 |
|---|---|---|---|---|---|---|---|---|
| **Proposed model** | 1599 | 831 | 377 | 193 | 0.81 | 0.8922 | 0.8092 | 0.8487 |
| **Mathematical model** | 755 | 850 | 1093 | 298 | 0.5357 | 0.7169 | 0.4085 | 0.5205 |

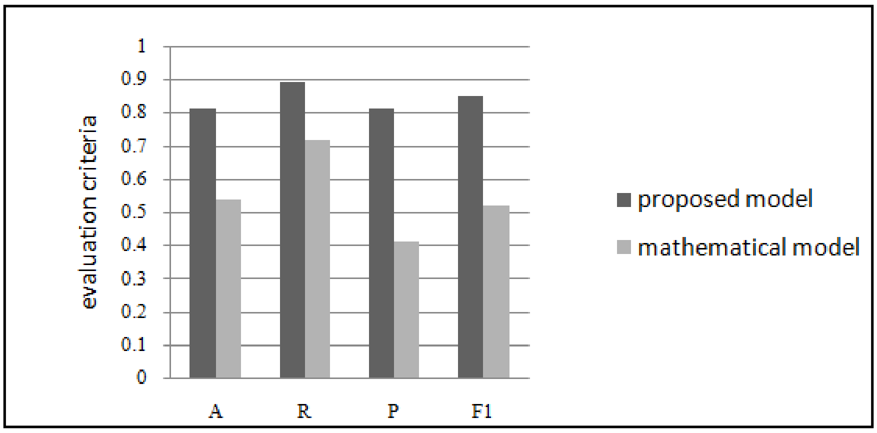


Figure 6 . Comparing the proposed method with mathematical model

According to the results of the simulation, the proposed algorithm compared with the mathematical model provided more appropriate assessment criteria to derive relationships.

Improved assessment reasons can be presented briefly as below:

Looking specifically at individuals with regard to the individual characteristics in each pre-processing of the data. As mentioned in the pre-processing section for pre-processing data of each record of the data set, the information in the profile of each of the caller and the callee is used.

Exploiting of individual characteristics and behavior According to the final aim of inference, that is identifying the relationships and friendship between people, certainly individual and behavioral similarities between the two who have the same points in common would be identified easier.

The use of fuzzy rules as mentioned earlier, the uncertainty in concepts in the context of mobile phone and its sensors. Certainly, fuzzy logic very powerful and flexible tool for modeling this uncertainty that can help us in order to deal with concepts in the real world.

Creation of Bayesian network with valid data. Unlike other works in this area, which network mostly relies on experienced experts or is manually mapped, this network and its dependencies between parameters have been identified with the training data.

## V. CONCLUSIONS AND RECOMMENDATION FOR FUTURE WORKS

This study aims to identify the user friendship that can create social networks and can be used in many applications as well as friendship proposing applications. In this study, Bayesian networks as a practical approach to modeling of user information is used to identify relationships. In the manufacturing process of Bayesian network and the preparation of training data and their preprocess, according to the characteristics of each individual a proper approach is considered that led to better results. According to the results, it can be concluded that Bayesian networks can be a good choice for modeling information to identify friendship relationships, which based on them we can say what kind of relation it is. Since the database used is related to the people in an organization, an enterprise social network was created that analyzing its relationships can be very efficient in making management decisions in large organizations. Now some of the managers in key organization have created related social networks and with the analysis and identification of important and effective people, most of human resources management procedures have been defined.

### A. *Future works*

As the proposed work, it can be said that the rising the features of a transaction can reveal more sophisticated behaviors of customers. For example, studying the feature of time of the transactions could led to analyze and extract the bestseller products and relations between 8 am to 10.On the other hand, the information of customers can discover a good relationship, although access to users' information due to privacy issues generally is not possible. To improve the quality of the proposed results followings are suggested:

Using Bluetooth connectivity information and other communicational information : In this study, only voice calls and SMS were investigated. In the future, you can use connection information of two devices for transmission of data files via Bluetooth or WiFi to complete the data or assess their impact.

Using information, such as the Facebook or other mobile social networking: using behaviors and relationships in cyberspace can be effective to identify the relations of friendship and its depth [19].

Improving the approach to determine the behavioral similarities between people: Now the behavioral similarities between the two men is obtained through fuzzy inference. Because values are Fuzzy material, it can be researched further and more accurately to identify the similarities between the two individual.

Assessing the effects of factors in making the Bayesian network: In this study, effect of factors on the network has not been investigated that can be studied in the future.

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