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Research Article

A Novel Dynamic Novel Growth model for Mobile Social Networks

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Abstract: With the rapid advancement of mobile networking technology and the widespread availability of high-speed data connectivity, mobile phones have evolved into potent platforms for social networking. Macro von Arb et al. proposed a serverless friend-of-friend detection algorithm, successfully implemented on VENETA, a mobile social networking platform. In our analytical study, we delved into two fundamental aspects of social network analysis: vertex degree distribution and clustering coefficient. These metrics provide crucial insights into the connectivity patterns and community structures within the network. By scrutinizing these metrics in the context of the implemented algorithm, we aim to assess its effectiveness in fostering connections and facilitating social interactions among users on the platform.

Keywords: Veneta; serverless; friend of friend detection; mobile social networking; vertex degree distribution; initial contact.

1 Introduction

Developing a novel dynamic growth model for mobile social networks entails considering numerous factors, including user interactions and the evolving landscape of mobile communication. The advent of 3G technology has significantly enhanced data transfer speeds in mobile networking, expanding the utility of mobile phones beyond traditional functionalities like calls and SMS to encompass data storage, transfer, and social networking. Presently, a plethora of mobile-based social networking systems have emerged, encompassing diverse functionalities such as location-based networking and mobile-specific interactions. Among these, VENETA and Proxy Dating stand out for their unique approach of circumventing reliance on GPRS-based internet protocols. Instead, they leverage short-range Bluetooth connectivity, thus offering cost-free communication. VENETA further distinguishes itself by implementing an advanced friend-of-friend detection algorithm, enhancing its networking capabilities.

In our study, we have conducted a thorough analytical examination of this algorithm, focusing particularly on two fundamental aspects of social network analysis: vertex degree distribution and clustering coefficient. Vertex degree distribution refers to the distribution of connections that each node (or vertex) in the network has. Understanding this distribution provides insights into the connectivity patterns within the social network. By analyzing the vertex degree distribution, we can uncover whether the network follows a specific pattern, such as a power-law distribution commonly observed in many social networks.

A network's clustering coefficient indicates how tightly connected nodes are. It measures the probability that two of a node's neighbours are related to one another. A high clustering coefficient denotes the emergence of closely linked clusters inside the network or a high degree of local clustering. Analyzing the clustering coefficient helps us understand the level of cohesion and the presence of community structures within the social network.

By studying these analytical metrics in the context of the serverless friend-of-friend detection algorithm implemented on VENETA, we aim to gain deeper insights into the network's structural properties and dynamics. This analysis can inform us about the effectiveness of the algorithm in fostering connections between users and facilitating social interactions within the mobile social networking platform.

Friend-of-friend detection within mobile systems serves as an indispensable tool in numerous daily life situations. Consider a scenario where one finds themselves in a new location devoid of immediate contacts. Instead of reaching out to each friend individually via phone calls, activating Bluetooth to search for friends of friends significantly expedites the process of establishing connections. This functionality becomes especially crucial during emergencies, such as medical crises, where time is of the essence. By leveraging friend-of-friend detection, individuals can swiftly reach out to extended social circles for assistance and support, enhancing overall safety and well-being.

Calculating the clustering coefficient and vertex degree distribution was made interesting by Ting Sun et al.'s proposal of ilife, a novel mobile social network service [3]. which deals with using a mobile device to search for a variety of life-related information, such as where to get food, clothes, shelter, and transportation, as well as another location-based social networking service?

If one could supplement the friend detection algorithm described earlier with data about a person's degree of vertex, or the amount of friends they have, along with their interests and hobbies, it would be relatively easy to find the most influential person in one's neighborhood who shares similar interests and hobbies [3]. Finally, we have shown simulation results displaying numerical data on the change in degree of vertex and change in number of triangles, which is relevant because we have introduced friend of friend detection and friend of friend of friend also possible to detect [12] using mobile.

Here's a broad outline for creating a dynamic growth model:

User Behavior and Interaction:

Define user behaviors: Understand how users interact within the mobile social network. Consider actions like friend requests, message exchanges, content sharing, and group formation.

Model user preferences: Incorporate user preferences, interests, and activity patterns into the growth model. This can be based on historical data or machine learning algorithms predicting user behavior.

Dynamic Evolution: Time-dependent parameters: Introduce time-dependent parameters to capture the evolving nature of the network. Users' activity levels, interests, and connections may change over time.

Adaptable network structure: Allow the network structure to adapt based on changes in user behavior and preferences. This could involve the creation and dissolution of connections or the emergence of new network clusters.

Validation and Optimization: Validate with real-world data: Test the growth model using real-world data or simulations to ensure that it accurately represents the characteristics of mobile social networks.

2 Network Growth Algorithm

The algorithm proposed by Marco von Arb et al. [1]. Is as fallows, Alice (A) owns a set X = $x_1.....x_N \subset V$ and Bob (B) owns a Set Y = $y_1.....y_M \subset V$. Here, X represents the phone numbers in Alice's and Bob's contact books, respectively, and V is the set of all 107 possible phone numbers that X could be.

1) $A \rightarrow B : E_\alpha(x_1),.........E_\alpha(x_N)$ (α Randomly chosen)

2) $B \rightarrow A : E_\beta(y_1),.........E_\beta(y_M)$ (β Randomly chosen)

3) $A \rightarrow B : E_\alpha(E_\beta(y_1)),........,E_\alpha(E_\beta(y_M))$

4) $B \rightarrow A : E_\beta(E_\alpha(x_1)),........,E_\beta(E_\alpha(x_N))$

5) Both, A and B, can compare the lists from step 3 and 4. Due to the commutatively assumption, If $x_i = y_i$ then

$$E_\beta(E_\alpha(x_i)) = E_\alpha(E_\beta(y_j))$$

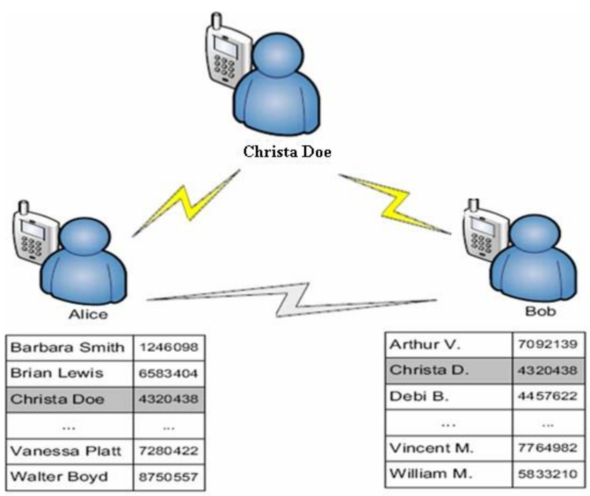

Figure1: Finding friends of friends [1]: Two strangers' mobile phones can compare each other's contact lists whenever they are within connection range.

The two strangers are told they are friends of friends if a matched entry is discovered. In this case, Alice and Bob have discovered a possible social network that draws data from contact books; they are searching for friends of friends on this network. Since both stringers added Crista Deo as a friend in their contact lists, it follows that they are mutual acquaintances based on their mobile numbers.

In general, we can choose any friend of a friend who is detected to be in our vicinity by using this algorithm: let mr ≥ S number of people in our contacts list (of N persons) each found to have ms ≥ 0 number of other friends. As a result, our algorithm begins with fallows [4].

1) Begin with an N-vertice seed network.
2) Establish an average first contact with Mr.
3) As a secondary contact, randomly select an average ms ms 0 neighbour of each first contact.
4) Connect the arc as a secondary interaction between two strangers.
5) Continue to follow steps 2-4 until the network reaches the appropriate size (fig. 2)

In the end, the analytical findings are useless.

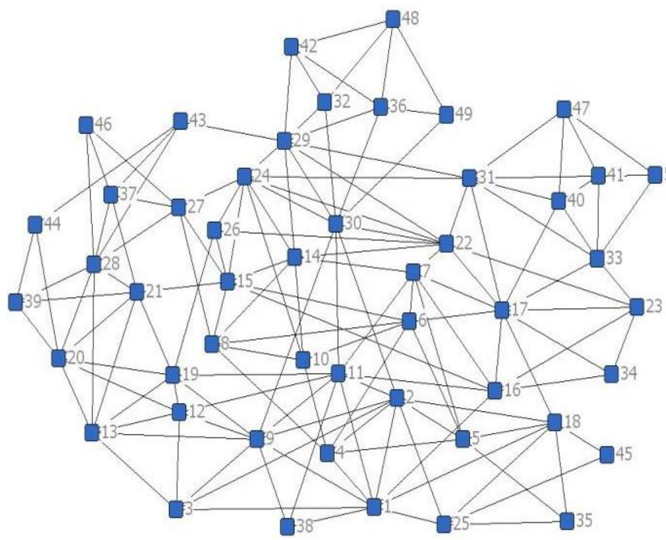

Figure2: Shows mobile social network graph

3 Vertex Degree Distributions

An equation is developed to control the average change in a vertex's degree during a single time step of the network's growth. Two separate mechanisms contribute to the increase of the degree (ki) of vertex vi. [4]:

Direct Linking: When a new vertex forms a direct connection with vi. Given an average of ~ t vertices at any time t, mr out of these are selected with a probability of m_r/t.

Secondary Contact Linking: When a vertex establishes a connection with vi as a secondary contact, leading to implicit preferential attachment. This results in a total of $m_r * m_s$ connections

As a result of these operations, we get the rate equation for vi's degree: [4,13]:

$$\frac{\partial k_i}{\partial t} = m_r\left(\frac{1}{t} + m_s\frac{k_i}{\sum k}\right) = \frac{1}{t}\left(m_r + \frac{m_s}{2(1+m_s)}k_i\right)$$

(1)

From this the probability density distribution for the degree k is given by

$$P(k) = AB^{A}(k+C)^{-2/m_s+2m_s m_r^{-3}}$$

Where

$$A = 2(1+m_s)/m_s, B = m_r(A+1+m_s), C = Am_r$$

4 Clustering Spectrum

The rate equation method has been used in earlier studies to determine the clustering coefficient, which quantifies the degree to which nodes in a network tend to cluster together [5–13]. This method allows us to analyze how the clustering coefficient changes based on the degrees of the vertices in the network.

We then investigate the time-dependent variation in the number of triangles encircling a given vertex, vi. Triangles in a network are fundamental components that signify connections between three vertices. The evolution of triangles around v_i is crucial for understanding the local clustering and connectivity patterns within the network.

The formation of triangles around v_i primarily occurs through two distinct processes:

1. Initially, vertex vi is selected as one of the initial contacts with a probability determined by the ratio mr/t, where mr represents the number of triangles formed by v_i's neighbors and t denotes the total number of triangles in the network. This process reflects the initial establishment of connections involving v_i.
2. Subsequently, when a new vertex joins the network, it links to some of v_i's neighbors, thereby creating additional connections and giving rise to new triangles. This process contributes to the ongoing evolution of the network structure and the formation of complex connectivity patterns.

By examining these processes in detail, we can gain insights into how local interactions and connections between vertices contribute to the overall topology and clustering characteristics of the network over time. The pace characterizes both of these procedures.

$$\frac{\partial E_i(k_i,t)}{\partial t}=\frac{m_r m_s}{t}+m_r m_s\frac{k_i}{\sum k}=\frac{\partial k_i}{\partial t}+\frac{m_r(m_s-1)}{t} \quad (2)$$

We get the time evaluation of triangles around a vertex v_i as

$$E_i(t)=k_i(t)+m_r(m_s-1)\ln\left(\frac{t}{t_i}\right)-m_r$$

From this we can obtain the clustering the coefficient as [2]

$$c_i(k_i)=\frac{2E_i(k_i)}{k_i(k_i-1)}=2\frac{k_i+D\ln(k_i+C)-F}{k_i(k_i-1)}$$

Where $C=Am_r, D=C(m_s-1), F=D\ln B+m_r$ For large values of degree k, the clustering coefficient thus depends on k as $c(k) \sim 1/k$.

5 Results

We counted the primary and secondary contacts for each individual in a model network we built with fifty nodes (Fig. 1) for the simulation part. Table 1 shows the results of dividing each person's total number of nodes by their ratio of secondary contacts and initial contacts, with a total of 50 nodes for each person.

When one person befriends someone else's friend, a triangle forms in the network. This is in contrast to the case of friendship alone. It is through a secondary interaction that this triangle forms. Additionally, there's a chance that a triangle will emerge out of the three initial contacts, meaning that two people on our contacts list might be friends even if we're not aware of it. When compared to the triangle formation that occurs when a friend of a friend becomes a friend figure, the likelihood of a new triangle forming is quite low.As the network expands, figure 2 illustrates the vertex degree distribution with node count. In this case, the yellow line shows the overall degree of nodes, the red line shows the degree owing to secondary contacts, and the blue line indicates the degree due to original contacts. This demonstrates unequivocally how secondary contact, or befriending a friend as a friend, affects the degree of vertex.

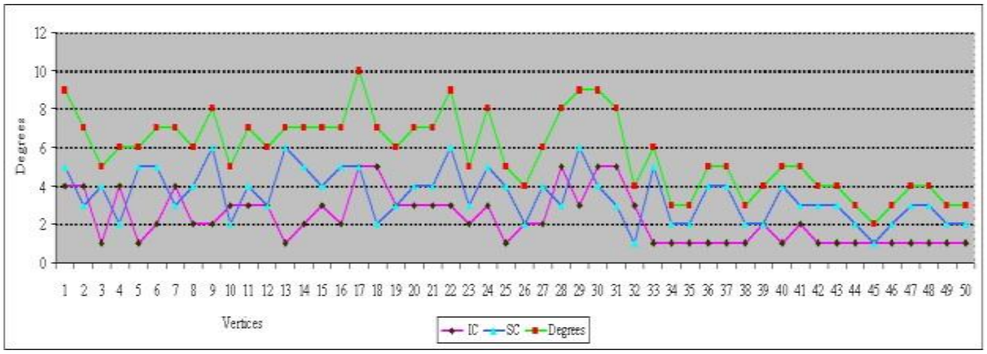

Figure.3: display of compared results of growing network community shows that, when initial and secondary contacts connect to a vertex vi, the initial contact grows much more slowly than the secondary contact, i.e., ♦ indicates the initial contact, ▲ indicates secondary contacts, and ■ indicates the degree of each vertex.

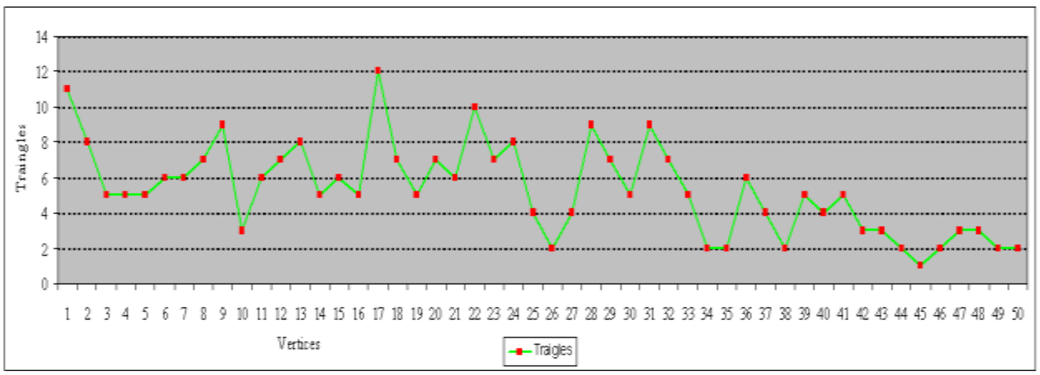

Figure 4: shows the distribution of all degrees as a function of the number of vertices.

The insertion of a friend of a friend as a secondary contact has led to a significant increase in the degree of vertex and number of triangles, as the table and figures make clear.

Table 1: Shows the contact differences

	Initial Friend (IC)	Secondary Contacts (SC)	Difference
Vertices	2.28	3.48	1.2
Triangles	0.2	5.34 %	5.14

Secondary contact is being used more often in the growth of mobile social networks than original contact.

6. Conclusions

Our mobile social network model has accomplished many noteworthy goals, including the ability to differentiate between different types of mobile community structures, assortative mixing, strong clustering, short average path length, and wide degree distribution. Through simulation results, we have demonstrated the efficacy of leveraging secondary contacts for network growth, showcasing superior expansion compared to primary contact utilization. This model, as introduced earlier, holds promise for integration into VENETA, complementing Marco van Arb's proposed framework [1], which operates independently of service providers and utilizes Bluetooth technology, thereby competing with the iLife model proposed by Ting Sun et al., a mobile internet-based service.

Tools:

At VENETA (www.veneta-project.net), you can see the results of our friend-of-friend detections, which were created using UciNet, NetDraw, and Excel.

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References

[1] M. Arb, M. Bader, M. Kuhn and R. Wattenhofer, “VENETA: Serverless Friend-of- Friend Detection in Mobile Social Networking,” *In IEEE International Conference on Wireless & Mobile Computing, Networking & Communication*, Avignon, France, 2008.

[2] J. Clerk Maxwell, “A Treatise on Electricity and Magnetism,” *Oxford: Clarendon*, vol.2, pp.68–73, 1892.

[3] T.Sun, X. Shi, Y. Shen, K. Li and W. Qu “ilife: A novel mobile social network services on mobile phone,” *2010 10th IEEE International Conference on Computer and Information Technology*, Bradford, UK, 2010.

[4] R. Toivonen, J.P. Onnela, J. S.¨ki, J. Hyvonen and K. Kaski “A model for social networks,” *Physica A*, vol. 371, pp.851–860, 2006.

[5] F. S. Tsai, W. Han, J. Xu and H.C. Chua “Design and development of a mobile peer-to-peer social networking application” *Expert Systems with Applications*, vol. 36, pp.11077–11087, 2009.

[6] M. J. Freedman, K. Nissim, and B. Pinkas, “Efficient Private Matching and Set Intersection” *Eurocrypt*, Berlin, Heidelberg, pp.1–19, 2004.

[7] S. Hohenberger and S. A. Weis, “Honest-Verifier Private Disjointness Testing Without Random Oracles,” *In Privacy Enhancing Technologies*, pp. 277–294, 2006

[8] Kiayias and A. Mitrofanova, “Testing Disjointness of Private Datasets,” *In Financial Cryptography*, pp. 109– 124, 2005.

[9] P. Krapivsky and S. Redner, “Organization of growing random networks,” *Phys. Rev. E*, vol. 63, 2001.

[10] S. Dorogovtsev, J. Mendes, A. Samukhin, “Structure of Growing Networks with Preferential Linking” *Phys. Rev. Lett*., vol.85, no.4633, 2000.

[11] G. Szabo´, M. Alava and J. Kerte´sz, “Structural transitions in scale-free networks,” *Phys. Rev. E*, vol.67, no.056102, 2000.

[12] S. Bhukya, “A novel model for social network,” *2011 Baltic Congress on Future Internet and Communications*, Riga, Latvia, pp. 21-24, 2011.

[13] S. Bhukya, “Discover academic experts in novel social network model,” *2011 International Conference on Advances in Social Networks Analysis and Mining*, Kaohsiung, Taiwan, 2011.