FRIENDSHIP INFERENCE IN MOBILE SOCIAL NETWORK: EXPLOITING MULTI-SOURCE INFORMATION WITH TWO-STAGE DEEP LEARNING FRAMEWORK

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Abstract- With the tremendous growth of mobile social networks (MSNs), people are highly relying on it to connect with friends and further expand their social circles. However, the conventional friendship inference techniques have issues handling such a large yet sparse multi-source data. The related friend recommendation systems are therefore suffering from reduced accuracy and limited scalability. To address this issue, we propose a Two-stage Deep learning framework for Friendship Inference, namely TDFI. This approach enables MSNs to exploit multi-source information simultaneously, rather than hierarchically. Therefore, there is no need to manually set which information is more important and the order in which the various information is applied. In details, we apply an Extended Adjacency Matrix (EAM) to represent the multi-source information. We then adopt an improved Deep Auto-Encoder Network (iDAEN) to extract the fused feature vector for each user. Our framework also provides an improved Deep Siamese Network (iDSN) to measure user similarity. To provide a substantial description and evaluation of the proposed methodology, we evaluate the effectiveness and robustness on three large-scale real-world datasets. Trace-driven evaluation results demonstrate that TDFI can effectively handle the sparse multi-source data while providing better accuracy for friendship inference. Through the comparison with numerous state-of-the-art methods, we find that TDFI can achieve superior performance via real-world multi-source information. Meanwhile, it demonstrates that the proposed pipeline can not only integrate structural information and attribute information, but also be compatible with different attribute information, which further enhances the overall applicability of friend-recommendation systems under information-rich MSNs

Keywords: . Extended Adjacency Matrix (EAM), TDFI, Siamese Network (iDSN)

I. INTRODUCTION

IN THE past decade, the mobile Internet has profoundly promoted the prosperity of mobile social networks (MSNs) [1], [2], [3]. According to the global digital population statistics as of April 2020 [4], over 4.2 billion people constitute unique mobile Internet users, encompassing 91.9% of the global active Internet users. The number of active mobile social media users has also exceeded 3.76 billion, up to 98.7% of the active social media users. Meanwhile, each mobile social service provider is accelerating the expansion of its user base to occupy a broader market. For example, the number of daily active *Instagram* users is up to a staggering increase from 400 millions in June 2018 to 500 millions in January 2019 [5]. These users not only use social media to find information, watch movies, buy and sell products, but also highly rely on it to connect with others and expand their social circles. Under such an incredible large-scale MSN, however, it is impossible for mobile social service providers to check the information of each user and quickly pinpoint their potential friends. This requires relevant MSNs to have the ability to automatically match potential friends. Consequently, friend-recommendation service has been widely adopted by most mobile social service providers, like *Facebook*, *Instagram*, and *Twitter* [6]. Finding the accurate potential friend relationship among all the social media users is like searching for a needle in a haystack. To reduce such complexity, conventional friendship-inference methods mainly depend on mutual friends, which provides long potential friend lists with very low precision [6]. In particular, friend-recommendation based on social graph representation [7], [8], [9], [10] is largely exploited. However, real-world mobile social networks are much more sparse than expected [11], [12], [13] (*i.e.*, the number of true friends is much smaller than that of nonfriends, as illustrated in Table III), which poses a challengeto existing approaches. Moreover, friend information is highly privacy-sensitive and deeply connected with our social identity [14], [15], [16]. More and more people choose to hide their friend information, such that the social network we can build become more sparse. For example, almost 17.2% *Facebook* users in New York hid their friend information in 2010 [17]. Worse more, these approaches cannot fully reflect the real preferences on friend selection [18]. This is due to the fact regarding missing of important real-world information such as users' different lifestyles [19], interests [20], and locations [21].

i i RELATED WORK

1. Deep Learning for Social Network Analysis: A Survey by Shang et al. (2017) This survey provides an overview of deep learning techniques applied to social network analysis, including friendship inference. It covers various architectures and methodologies used in modeling social networks and inferring relationships.

2. **Friendship Prediction in Social Networks Based on Deep Learning Methods by Zhang et al. (2018)** This paper explores the application of deep learning methods, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for friendship prediction in social networks. It discusses the challenges and opportunities in utilizing deep learning for inferring friendships.

3. Multi-Source Social Data Fusion for Friendship Prediction by Li et al. (2019) The paper investigates the fusion of multi-source social data, such as call logs, text messages, and social media interactions, for friendship prediction. It proposes a fusion framework and evaluates its effectiveness in inferring friendships in mobile social networks.

4. Graph Convolutional Networks for Friendship Prediction in Mobile Social Networks by Wang et al. (2020) This study focuses on the application of graph convolutional networks (GCNs) for friendship prediction in mobile social networks. It explores the effectiveness of GCNs in capturing the structural information and relationship dynamics inherent in social networks.

5. Exploiting Multi-Source Information for Friendship Inference in Online Social Networks by Liu et al. (2021) The paper presents a comprehensive approach for friendship inference in online social networks by exploiting multi-source information. It discusses the integration of various data sources and the development of machine learning models for accurate inference.

6. Deep Learning for Social Network Inference by Hamilton et al. (2017) This survey covers deep learning techniques for social network inference, including friendship prediction. It discusses the challenges in modeling social networks and highlights recent advancements in deep learning methodologies.

7. Friendship Prediction Based on Mobile Social Network Data by Chen et al. (2019) The study investigates friendship prediction based on mobile social network data, including call logs and text messages. It proposes a framework for feature extraction and machine learning-based prediction of friendships in mobile social networks.

8. Predicting Friendships Using Mobile Phone Data by Eagle et al. (2009) This seminal paper explores the use of mobile phone data for predicting friendships. It analyzes call and text message patterns to infer social relationships and discusses the implications for understanding social dynamics in mobile networks.

9. Friendship Inference in Social Networks: A Survey by Jin et al. (2011) This survey provides an overview of friendship inference techniques in social networks, including approaches based on machine learning and data mining. It discusses the challenges, methodologies, and applications of friendship inference in various domains.

10. Combining Multiple Social Networks for Friendship Prediction by Tang et al. (2015) The paper presents a method for combining information from multiple social networks, such as Facebook and Twitter, for friendship prediction. It discusses the fusion of heterogeneous data sources and the integration of machine learning techniques for improved inference accuracy.

III METHODOLOGY

1. Data Sources and Preprocessing:

- Detailed description of each data source.
- Preprocessing steps for each data source:
  - Data cleaning.
  - Feature extraction.
  - Data integration.

2. Two-Stage Deep Learning Framework:

- Stage 1: Feature Extraction:
  - Description of the deep learning model architecture (e.g., CNN, RNN).
  - Input data format.
  - Training procedure.
- Stage 2: Friendship Inference:
  - Description of the deep learning model architecture for inference.
  - Input features.
  - Output format.
  - Training and inference procedure.

3. Integration and Deployment:

- How the two-stage framework integrates with the overall system.
- Deployment considerations (e.g., scalability, real-time processing).

4. Evaluation Metrics:

- Metrics used to evaluate the performance of the system (e.g., accuracy, precision, recall).

- Experimental setup (data sets, training-validation-testing splits).

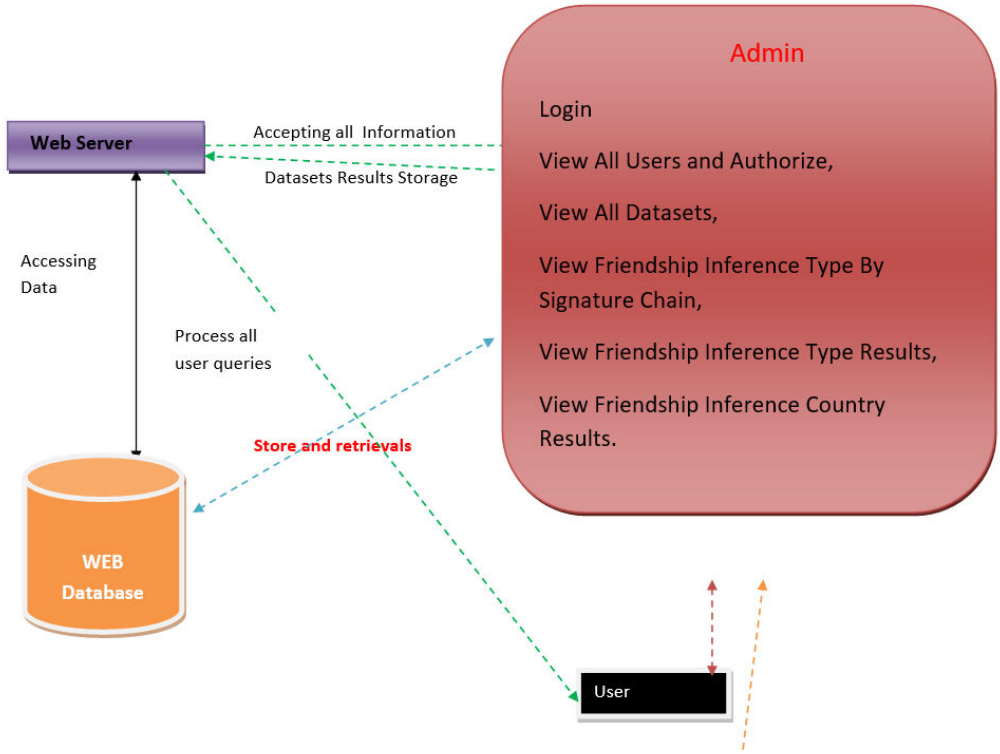
5. Results and Discussion:

- Presentation of experimental results.
- Comparison with existing methods if applicable.
- Discussion of findings and insights.

IV PROPOSE SYSTEM & IMPLEMENTATION

The multi-source information. Note that from the overall perspective of mobile social networks, friend relationships are structural information. On the contrary, from a local perspective of each user, which friends the user has can also be regarded as a kind of attribute information. Location is another common attribute information, because it is a property that naturally exists with MSNs, and location sharing services (e.g., check-in service) are already built into most MSN applications. Meanwhile, location information can further reflect the user's behaviors, which is very representative. Eagle et al. [21] confirmed that data such as location information obtained through mobile devices has extraordinary potential in social network analysis. And Scellato et al. [27] also indicated that synchronous check-ins information among users can imply potential friendship. Additionally, Backes et al. [23] found that check-in information can denote the mobility characteristics, which are significant for inferring friendship.

With the cooperation of two DL-based modules, our proposed pipeline can not only integrate structural information and attribute information, but also be compatible with different attribute information. It is worth noting that the location information is applied as a case study, TDFI has good scalability and can incrementally consider different categories of information while obtaining a reasonable complexity. For the purpose of facilitating real world deployment, the effectiveness and robustness of TDFI are carefully evaluated on three large-scale real-world datasets collected from Instagram [23]. Furthermore, the trace-driven comparison has demonstrated that the newly proposed TDFI can effectively cope with the ubiquitous sparse problem in MSNs, and significantly outperforms numerous state-of-the art methods for friendship inference.



Register and Login,

View Profile,

Upload Datasets,

Find Friendship Inference Type,

Find Friendship Inference Type By Hash code Signature.

Figure 1: Proposed system architecture

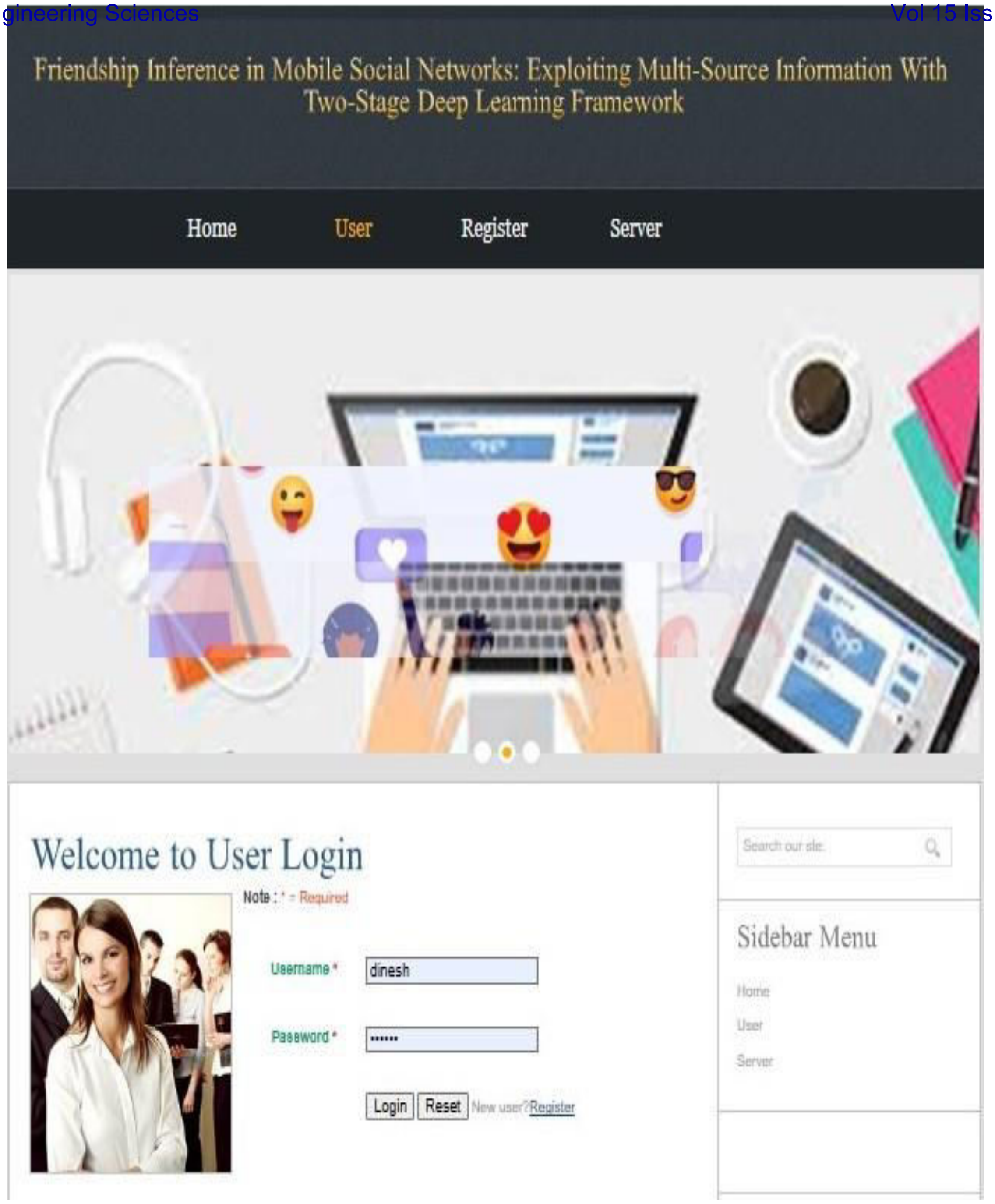
V RESULT ANALYSIS

HOME PAGE

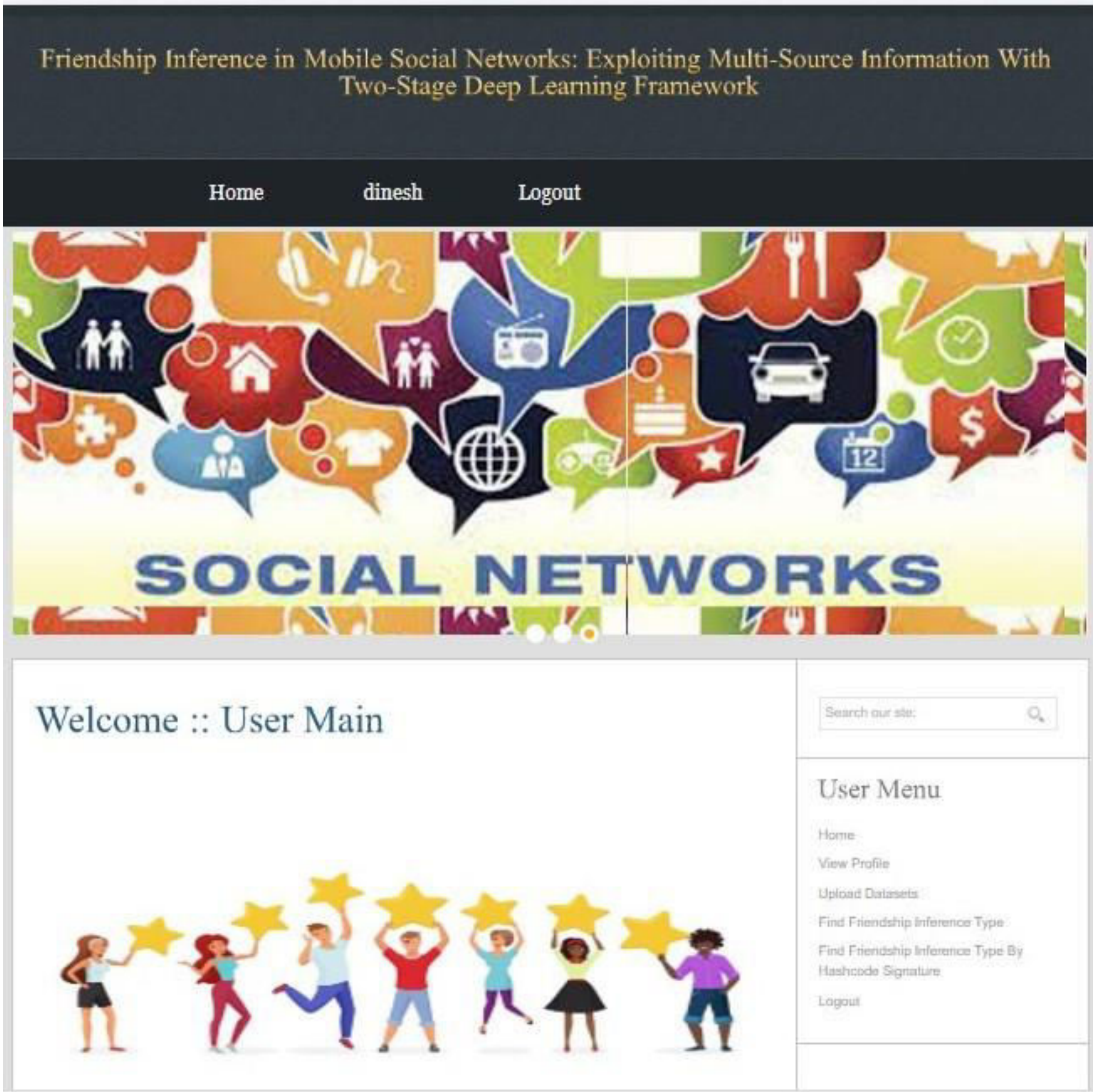
SERVER LOGIN PAGE

SERVER PAGE LOGIN

USER LOGIN PAGE


Friendship Inference in Mobile Social Networks: Exploiting Multi-Source Information With Two-Stage Deep Learning Framework
Home
User
Register
Server
Welcome to User Login
Note : * = Required
Username *
dinesh
Password *
Login
Reset
New user? Register
Search our site
Sidebar Menu
Home
User
Server

USER PAGE



VI CONCLUSION

Motivated by the diversification of social forms and various data with mobile social networks, we proposed, implemented, and evaluated TDFI, a novel two-stage deep learning framework for friendship inference. Our TDFI enables MSNs to smartly exploit multi-source user-related data simultaneously, rather than hierarchically. In terms of details, we first adopted an extended adjacency matrix with both local and global normalizations for absorbing different information. This matrix then serves as an input to the IDAEN network to extract fused feature with low dimensionality. After that, the Idsn network is utilized to determine whether the pair of users has friendship by measuring the similarity of the fused feature. We conducted extensive experiments on three real-world datasets to evaluate the performance of TDFI and baseline methods. The trace-driven evaluation results demonstrated that TDFI can complement the advantages of different information, avoiding the performance issues caused by insufficient single source information. In addition to being compatible with structural information and attribute information simultaneously, our TDFI can also exploit different attribute information. Overall, our qualitative and quantitative evaluations indicated that the newly proposed TDFI outperforms the existing recommendation systems with improved accuracy and robustness. Regarding future work, an interesting open issue is whether our framework can be extended to the cooperation of different mobile social networks.

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