



Predicting User Behavior Using Foursquare Data

Ms. G.Umadevi (M.C.A). Rajeev Gandhi Memorial college Of Engineering and Technology, Nandyal

*Mr.K.R.HARINATH MTech, (Ph.D.) Rajeev Gandhi Memorial college Of Engineering and Technology, Nandyal

Abstract

Without relying on the social network data, our method offers a precise and practical mechanism for third-party application providers to identify whether a Foursquare user is influential. With regard to global social connectivity, content publication behavior, and the prediction of social influence, our study offers a systematic knowledge of Foursquare, the typical LBSN service. The analytical findings are beneficial for various pertinent entities: 1) When we look at Foursquare or other LBSN service providers globally, we gain a thorough picture of the social relationships. To put it another way, we create and examine the worldwide Foursquare social network, which has more than 60 million members. This graph is useful for researching how Foursquare spreads information and fosters social interactions. In the meanwhile, by consulting user profiles and published advice, We are aware of the global geographic distributions of users and locations. We also look at how user activity has changed over time. All of these details can help LBSN service providers plan resource provisioning to efficiently and scalability serve millions of customers. Additionally, they can extract user thoughts and actions by looking at the provided tips. The tip data may also be used for user profiling and venue recommendations; 2) To characterize the traffic patterns of LBSNs, Internet service providers (ISPs) can apply an evolutionary perspective to understand the geographic distribution, content generating behavior, and interaction patterns of users.

1. INTRODUCTION

1.1 Introduction

Location-based social networks (LBSNs) like Foursquare [18], [42], [43], [47], [57], Yelp [23], [65], and Dianping [17], [27] have experienced substantial growth due to the quick development of mobile computing technology and social networking services. These networks not only facilitate user interaction but also provide location-specific features. This service keeps track of a wide range of user data, including social connections between users, geographic and chronological details of user activity, and user-expressed opinions. To forecast the movement of a sizable number of users, one can use the comprehensive LBSN data. Despite being the most widely used LBSN, many crucial aspects of Foursquare remain unclear, such as how its users connect with one another globally. Aside from that Since the majority of current research only employ data from a biased group of Foursquare users, the analytical findings do not accurately reflect all Foursquare users. Researchers acquired the Foursquare data through Twitter, as was done in [26], [43], [47], and [49], as some Foursquare users have elected to automatically republish their postings on Twitter. Unfortunately, Foursquare users who have linked their accounts to Twitter are more active than other Foursquare users, as demonstrated by Gong et al. [18]. In greater depth, those who have connected their Twitter accounts tend to submit more tips and check-ins and have more followers and follows overall. Therefore, if we only use Twitter to gather the Foursquare data, We can only collect user activity data from a subset of more active Foursquare users; the

associated data set cannot accurately represent the user activity of the full Foursquare user base.

2. Literature Survey

• Second, we concentrate on tips, which make up the bulk of Section III-B's Ugo Foursquare. Understanding user viewpoints, distributions, and movements is greatly aided by tips. However, a lot of the analytical works that are currently available are focused on the check-in activities [42], [43], [49], and [57]. Unfortunately, foursquare has stopped supporting the check-in feature since August 2014, and a study by Zhang et al. [67] found that around 75% of all check-ins don't correspond to actual user trajectories. The study of advice needs to be methodical. The interpretation of the tip texts is constrained since certain existing works [38], [54] concerning tips are based on the data set acquired in a biased manner. We suggest a thorough analysis based on all 55.18 million Foursquare tips that have been published to close this gap. First, we receive a statistical breakdown of the amount of tips posted by various user groups. We next delve deeper into each tip's text and examine it from the perspectives of the tip venues, temporal trends, and sentiments. Our statistical findings present the first thorough analysis of Foursquare tips. Last but not least, we suggest the concept of social influence prediction based on a user's profile and UGC as a real-world application scenario to assist third-party application providers. Numerous social influence metrics have historically been based on data regarding social connectivity, such as pagerank [34] and follower count [9]. However, several prominent online social networks (OSNs), including Facebook, allow users to hide their buddy lists these days. Therefore, we might not be able to tell whether from the standpoint of third-party application providers If the social graph information is incomplete, a user is influential. In Section III-C, we examine the connection between social influence, user profiles, and UGCs in order to address this issue. We can see that a user's profile contains a number of information fields that can be used, along with her content production habits, to determine whether or not she is influential. Based on this assumption, we develop a supervised machine learning-based model to determine a user's influence by looking at her profile and user-generated content (UGC). Our analysis reveals that our method can accurately identify the influentials, with an F1-score of 0.87 and an AUC value of 0.88. Our method offers a precise and practical technique, independent of Foursquare, for application developers to assess if a user is influential. on data from the social network. With regard to global social connectivity, content publication behavior, and the prediction of social influence, our study offers a systematic knowledge of Foursquare, the typical

LBSN service. The analytical outcomes are beneficial for various pertinent entities: 1) From a global perspective, we obtain a thorough grasp of the social connections for Foursquare itself or comparable LBSN service providers. To put it another way, we create and examine the worldwide Foursquare social network, which comprises 60 millions of users. This graph is useful for researching how Foursquare's social interactions and information diffusion work. We are aware of the geographic distributions of people and venues all over the world by using user profiles and publicly available tips. We also examine the development of user activity. The LBSN service providers can utilize all of these details to plan resource provisioning to accommodate millions of users at once.

3. OVERVIEW OF THE SYSTEM

3.1 Existing System

In 2009, Kwak et al. [34] examined the entire Twitter social graph, which comprised 41.7 million users. They examined the follower-following topology and discovered a number of characteristics that set Twitter apart from other social networks. In 2012, Watanabe et al. [59] gathered a Twitter social network with 469.9 million members and 28.7 billion relationships, and they examined the graph's degree distribution, reciprocity, degree of separation, and diameter. About 93.77% of the whole Twitter social graph was crawled by Gatilov et al. [16], who then examined its macrostructure.

3.1.1 Disadvantages of Existing System

The system is less effective due to lack of location-based social networks (LBSNs).

The system doesn't effective due to lack of social influence.

3.2 Proposed System

□ In the proposed study, Foursquare, the typical LBSN service, is presented with a systematic understanding of global social connectivity, content posting behavior, and social influence prediction. The analytical findings are beneficial for various pertinent entities: 1) When we look at Foursquare or other LBSN service providers globally, we gain a thorough picture of the social relationships. To put it another way, we create and examine the worldwide Foursquare social network, which has more than 60 million members. This graph is useful for researching how Foursquare spreads

6. CONCLUSION

✓ Based on the crawled data of all 61.43 million Foursquare users, we give a thorough analysis of user behavior in this paper. Our study examines social connections and tips, two essential components of Foursquare. We examine the entire Foursquare social network and present a number of novel and previously unknown properties of this enormous network, such as a moderate reciprocity (0.42), a low average clustering coefficient (0.065), a massive strongly connected component (covering almost 60% of users), and a significant community structure (Q value 0.6). Except for the singletons, practically all Foursquare users have only tenuous connections. We also do a thorough analysis of all Foursquare tips that have been posted. On the one hand, we examine the quantity of advice offered.

Future Enhancement

✓ Second, there are some rogue accounts on Foursquare that may post some false advice in an effort to deceive honest users. Nearly 30% of all users on Dianping, another prominent LBSN, are fraudulent identities, according to Gong et al. [17]. Even though foursquare has implemented various spam reporting and detection procedures, spam tips continue to surface. We will use machine learning technologies [17, 20] and social graph-based technologies [6, [55] to further examine the topic of malicious account detection.

7. References

- . Alrumayyan, S. Bawazeer, R. AlJurayyad, and M. Al-Razgan, "Analyzing user behaviors: A study of tips in Foursquare," in Proc. 5th Int. Symp. Data Mining Appl. , 2018, pp. 153–168.
- [2] S. Bird, "NLTK: The Natural Language Toolkit," in Proc. COLING/ACL ,2006, pp. 1–8.
- [3] V. D. Blondel, J.-L. Guillaume, R. Lambiotte, and E. Lefebvre, "Fast unfolding of communities in large networks," J. Stat. Mech. , vol. 2008, no. 10, Oct. 2008, Art. no. P10008.

[4] L. Breiman, "Random forests," Mach. Learn. , vol. 45, no. 1, pp. 5–32, 2001.

[5] A. Broder et al. , "Graph structure in the Web," Comput. Netw. , vol. 33, nos. 1–6, pp. 309–320, Jun. 2000.

[6] Q. Cao, M. Sirivianos, X. Yang, and T. Pregueiro, "Aiding the detection of fake accounts in large scale social online services," in Proc. NSDI ,2012, pp. 197–210.

[7] J. Capdevila, M. Arias, and A. Arratia, "GeoSRS: A hybrid social rec-ommender system for geolocated data," Inf. Syst. , vol. 57, pp. 111–128, Apr. 2016.

[8] E. Celikten, G. Le Falher, and M. Mathioudakis, "Modeling urban behavior by mining geotagged social data," IEEE Trans. Big Data , vol. 3, no. 2, pp. 220–233, Jun. 2017