Chapter 7
Community Detection and Profiling in Location-Based Social Networks

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ABSTRACT

Due to the proliferation of GPS-enabled smartphones, Location-Based Social Networking (LBSNs) services have been experiencing a remarkable growth over the last few years. Compared with traditional online social networks, a significant feature of LBSNs is the coexistence of both online and offline social interactions, providing a large-scale heterogeneous social network that is able to facilitate lots of academic studies. One possible study is to leverage both online and offline social ties for the recognition and profiling of community structures. In this chapter, the authors attempt to summarize some recent progress in the community detection problem based on LBSNs. In particular, starting with an empirical analysis on the characters of the LBSN data set, the authors present three different community detection approaches, namely, link-based community detection, content-based community detection, and hybrid community detection based on both links and contents. Meanwhile, they also address the community profiling problem, which is very useful in real-world applications.

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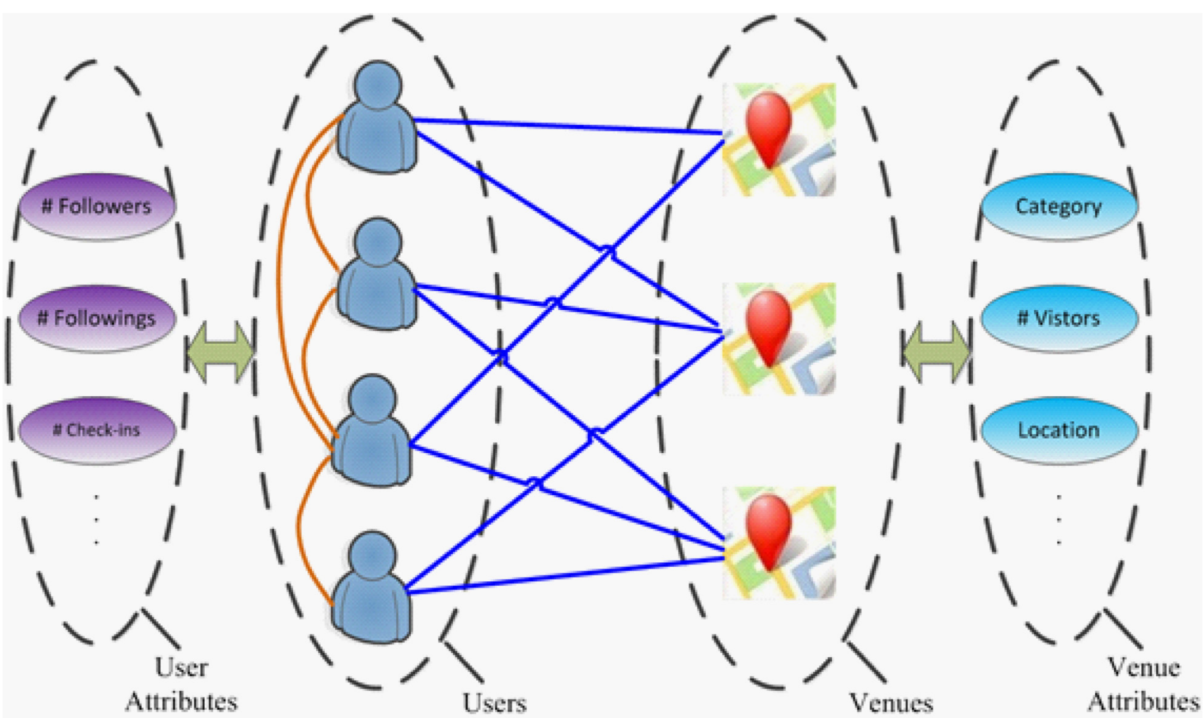
1. INTRODUCTION

The recent surge of location-based social networks (LBSNs, e.g., Foursquare and Facebook Places) driven by the increasing popularity of smart phones is bringing a new set of opportunities for research scientists and application developers. Compared with traditional online social networks (e.g., Facebook, Twitter), a distinct characteristic of LBSNs is the co-existence of both online and offline social interactions, as shown in Figure 1. On one hand, LBSNs support typical online social networking facilities, e.g., making friends, sharing comments and photos. On the other hand, LBSNs also support offline social interactions, e.g., checking in places. In other words, LBSNs are heterogeneous social networks which consist of both online and offline social links (Guo, Zhang, Wang, Yu & Zhou, 2013). Meanwhile, vertices in LBSNs usually have multiple attributes, e.g., attributes of a user might include number of followers, number of followings, and number of check-ins; a venue might have attributes such as category, number of check-ins and number of visitors.

One fundamental issue in social network analysis is to detect user communities. A community is typically thought of as a group of users who are densely interconnected compared to the other users in the network (Newman & Girvan, 2004; Fortunato, 2010). Specifically, discovering communities of LBSN users who visit similar physical places are able to facilitate many applications, such as direct marketing, friend recommendation, and community sensing (Zhang, Guo & Yu, 2011). However, unlike social networks (e.g., Flickr, Facebook) which provide explicit groups for users to subscribe or join, the notion of community in LBSNs is not well defined. In order to capitalize on the huge number of potential users, quality community detection and profiling approaches are needed.

Firstly, unlike social networks which only contain a single type of social interaction, the co-existence of online/offline social interactions

Figure 1. An example of LBSN



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