ABSTRACT

Location-based social networks (LBSNs) have witnessed a great expansion as an attractive form of social media. LBSNs allow users to “check-in” at geographical locations and share this information with friends. Indeed, with the spatial, temporal and social aspects of user patterns provided by LBSNs data, researchers have a promising opportunity for understanding human mobility dynamics, with the purpose of designing new generation mobile applications, including context-aware advertising and city-wide sensing applications. In this paper, the authors introduce a learning based random walk model (LBRW) combining user interests and “mobility homophily” for location recommendation in LBSNs. These properties are observed from a real-world Location-Based Social Networks (LBSNs) dataset. The authors present experimental evidence that validates LBRW and demonstrates the power of these inferred properties in improving location recommendation performance.

Keywords: Check-In Data, Data Mining, Location-based Social Network, Random Walk, Recommendation Systems, User Patterns

1. INTRODUCTION

Recently, with the advances in GPS-enabled devices, Wireless Networks and ubiquitous computing, online social networks or Location-Based Social Networks (LBSNs) such FourSquare, Gowalla and FaceBook Places have witnessed a rapid expansion largely among users and have attracted important researchers’ efforts, to investigate spatial, temporal and social aspects of user patterns. LBSNs allow users to “check-in” at geographical locations and share this information with friends.

This information offers a potential knowledge about users’ preferences on geographical locations. Therefore, it can help advertisers to build a personalized and efficient recommender system, in order to guide users exploring new locations. Typically, recommender systems are inevitable tools to filter and present relevant information to the users, helping them in their decision-making process. For instance, we have a set of users and a set of locations. Each user can rate the visited locations by a multiple-scale rating. The recommender system has to provide rating prediction for unvisited venues, and recommend venues that are already rated.

The most challenging aspect of this kind of recommender systems is the correlation between the facets of check-ins activities: user interests
and “mobility homophily”, understanding to what extent these facets can be exploited to identify and recommend personalized new locations to be discovered by the user.

To tackle the aforementioned challenging aspect, our work contributes by an approach for both location prediction and location recommendation. We develop a Learning Based Random Walker (LBRW) that obviously constructs a network which its structure and characteristics are inferred from LBSN data, particularly user interests and “mobility homophily”; with the aim to improve the location recommendation quality.

In Section 4, we analyze the Foursquare data and we discover that it exhibits the following interesting characteristics.

- **New Locations or Previously Unvisited Locations**: We discovered that 75.28% of users have check-ins in previously unvisited locations, while the average percentage of check-ins in unvisited locations is 71.41% (see Figure 5 and Figure 6, Section 4.1.).

- **Friends and Similarity**: In our data, 90% of users have 3.16% and 1.04% of common check-ins with friends and with all users respectively. This indicates that similarity in check-ins with friends exists; still this similarity is limited (see Figure 3 and Figure 4, Section 4.1.).

- **Matrix Sparsity**: From analyzing our data set, we have concluded that the user-location matrix density is about $7.81 \times 10^{-4}$, and the ratings matrix density is about $3.81 \times 10^{-2}$.

The rest of this paper is organized as follows. The next section gives some background on recommender systems and reviews related work in the literature. In section 3 we present LBRW, our enhanced Random Walker approach for location recommendation. The empirical study on the location recommendation algorithm upon large scale datasets crawled from Foursquare is detailed in Section 4. Finally, we conclude the paper and suggest future directions in Section 5.

2. RELATED WORK

Location based services have received unprecedented interest due to the potential knowledge offered by the spatial, temporal and social characteristics, allowing the growth of real-world challenging applications such as context-aware advertising and mobile recommender systems.

Recommender systems which are a type of personalized systems (Savage, Baranski, Chavez, & Höllerer, 2012) that filters information and presents a personalized and a relevant one; are one of the most important applications with regard to the high-value generated in either research or industry.

Velde (2008) designs an experience-based approach based on Nack’s definition of experience (Nack, 2003), with the aim of acquiring and representing the relevant aspects of user and location experience within the context of mobile recommendation systems.

Jamali and Ester (2009) propose TrustWalker which combines user trust network and the collaborative filtering approach into a random walker for item recommendation. The TrustWalker approach examines the user trust network to find trusted friends which rates item $i$ or items similar to $i$. Thus, the TrustWalker performs several random walks and aggregates the returned ratings of these random walks as the item rating prediction.

Hussein (2010) present the architecture and the implementation of the enhanced k-means based system for products recommendation. The enhanced k-means technique that minimizes the validity measure (ratio: intra-cluster measure / inter-cluster measure) along with the user ratings of products, can infer the appropriate recommendation.

In Leung, Lee, & Lee (2011), Leung et al. propose a Collaborative Location Recommendation (CLR) with the purpose of generating accurate location recommendation. The CLR process constructs a Community Location Model (CLM) graph, which integrates users, locations, activities to capture users’ trajectories. The CLR process continues with applying a Community-based Agglomerative-Divisive Clustering (CADC) on the CLM graph with
Irrigation Water Valuation Using Spatial Hedonic Models in GIS Environment
www.igi-global.com/chapter/irrigation-water-valuation-using-spatial/65018?camid=4v1a