Friendship and Mobility: User Movement in Location-Based Social Networks

Bhasya Maddukuri
Deepika Gangula
Snigdhitha Kasarla

Critique

Modeling of human mobility has wide range of applications like traffic prediction, ecology, epidemiology, urban planning etc.. Knowledge of users location can help improving large scale systems like mobile computing, mobile sensing, cloud computing and helps in choosing locations for business advertisement casting etc..

Despite their importance for so many applications, our understanding of the basic laws governing human motion remains limited owing to the lack of tools to monitor the time-resolved location of individuals. Understanding the human mobility is essential for deeper understanding of network dynamics and evolution.

In this paper the authors propose a coherent model for studying the main aspects of Human Mobility such as Geographic Movement, Temporal Dynamics and Social Networks. Short distance travelling is not effected by social network ties while long distance travel is influenced by social network ties.

The authors investigated patterns of human mobility on three large and different datasets. Out of which two are location based social network check-in data spanning the whole planet and the other data set is cell phone location data. Authors considered the location based social network check-in data from the Gowalla and Brightkite websites. These websites are no longer in existence. So any analysis over the data from these resources may be trusted or supported. Authors studied the problem of human mobility in location sharing services. They concentrated and worked on limited number of places like home and work.

Authors in this paper discuss the relative influence of a friend, where a friend who lives 1,000km away is 10 times greater than the influence of a friend who lives 40km away on a user making check-ins. On the other hand if it would have given better results or figures if they have considered a pair of users who live within the same state/province, and a pair of users in different states/provinces. In this case, we can have two cases one for friends who live in shorter distance and other case would be friends living longer distance.

Authors did not consider or discuss anything regarding the time-sensitivity. Instead of considering only the regular places or the places visited routinely like home and work, they could have considered the tourist places or popular landmarks. Also, considering the seasonal significant landmarks. Some places have most of the visitors during certain time slot. The probability of visitors visiting a famous landmark and then visiting the nearest landmarks is high. Authors did not discuss the routes and paths for these landmarks. They could have designed the best routes which are mostly adopted by people, in this way they could have gathered most check-ins from the famous landmarks and all the restaurants near by the landmark. The time-sensitivity route can be recommended, by designing a framework of routes to the famous landmarks with respect to the seasonal periods. As mentioned above, to find the next place with the proper visiting time, we should consider the amount of time spent on traveling from the current landmark to the next.

Consider an example, if a trip or visit is planned to a shopping mall which is 2 hours away. If there a museum in the midway which is 30 minutes away, the museum can be reached with transit of 30mins.

Authors also should have discusses about the order of visiting places. The visiting order of places is crucial as it depends on the nature of places and human preference. Some places are extremely sensitive to the visiting time, while the others might not have any strict constraint. The best design system should recommend a route that has high probability of visitors or which satisfies all the requirements of people. The data that is used by the authors can used to design a system which has all the above satisfying needs.

Authors suggested different models that include spatial, temporal, and social relation information for predicting human movement. These models are tough to extend to large number of contextual variables. The Gaussian mixture models discussed in the paper does not incorporate content at all. The existing work on mobility prediction points out to a need for improved, principled ways to exploit and integrate the potentially large number of contextual variables available on mobile devices like smartphones.

From the information gathered through different resources, we can differentiate user depending on their mobility as home-work, home-vacation, work-business trip, and work-conference. This can also help as most of the activity or mobility of people happens from home or work.

Along with the route design people can also be suggested about the quality restaurants near by the place visiting. This can be passed on very easily. I f one of your friend suggests you something, this is passed on at least 75% and so the probability of you visiting the place is high during your visit. And one more interesting aspect you can take into consideration is sports. Keeping track of the sports events and their locations, nearby landmarks and the probabilities can be high.

Before concluding, let us brief the pros and cons of the paper:

Pros:

- Supported most of the assumptions with clarified explanation.
- Clearly disagreed some of the assumptions and proved.

- The models explained are good enough.
- Over-all content of the paper is good, with enough assumptions, clarifications and models.

Cons:

- Important landmarks, famous visiting places are not considered, limited to only home and work.
- The data used for analysis is old and the resources are now not available to support.
- Seasonal importance should be considered.
- A design system should have explained considering the routes covering most of the nearby visiting places.
- Sports which has the most happening events is not taken into consideration.

The authors concluded saying that social network ties can explain about 10% to 30% of all human movement while periodic behavior explains the 50% to 70% based on the model developed human mobility that combines periodic short range movements with travel due to the social network structure.

References:

Xingjie Liu, Qi Hey, Yuanyuan Tiany, Wang-Chien Lee, John McPhersony, and Jiawei Han. Event-based social networks: Linking the online and offline social worlds. Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining, 2012.

Hsun-Ping Hsieh, Cheng-Te Li, and Shou-De Lin. Exploiting Large-Scale Check-in Data to Recommend Time-Sensitive Routes. Proceedings of the ACM SIGKDD International Workshop on Urban Computing, 2012.

Liangjie Hong, Amr Ahmed, Siva Gurumurthy , Alex Smola , and Kostas Tsioutsiouliklis. Discovering Geographical Topics In The Twitter Stream. Proceedings of the 21st international conference on World Wide Web, 2012.

Trinh Minh Tri Do and Daniel Gatica-Perez. Contextual Conditional Models for Smartphone-based Human Mobility Prediction. Proceedings of the 2012 ACM Conference on Ubiquitous Computing, 2012.

Marisa Vasconcelos, Saulo Ricci and Jussara Almeida. Tips, Dones and Todos: Uncovering User Profiles in Foursquare. Proceedings of the fifth ACM International Conference on Web Search and Data Mining, 2012.