

Detecting the Trajectory Community Based on the User Suggestion

¹POOJA K T, ² Dr. K. THIPPESWAMY

¹ M.Tech in CS&E, ² Professor and Chairman, DoS in CS&E

¹ VTU PG Centre, Mysuru,

² VTU PG Centre, Mysuru

Abstract: Data mining is an enactment of inspecting the enormous preceding databases in order to produce new information. In this paper we will be detecting communities from trajectories. In existing algorithm trajectory clustering is performed based on a single information source such as location data, regrettably additional information are ignored, due to these discovering the communities in trajectory data sets are not trustfully. To overcome these we proposed trajectory community for the multi-source scattered modeling based on the user recommendation. It combines additional information with raw trajectory data and fabricate the scattered process on multiple similitude metrics. Based on these scattered modeling we will be constructing the multi-modal scattered process and optimizing the heat kernel to learn the ordered kernel. Then compact sub-graph detection is used to discover the set of diverse communities. At last based on this information, we proposed a novel model for user recommendation.

IndexTerms - Trajectory, clustering, community, scattering.

I. INTRODUCTION

Now a day's everyone needs a social media to gather the information. When peoples are staying in different regions then getting or sharing the information about the social recommendation will be difficult, hence to overcome these, community are made, which helps to bring the people together and support each other in the fight to overcome those problems. Early days communities are detected by a social connection and by a graph division, but due to this privacy become the main problem and it is very difficult to capture connection in human society. To overcome these we started to capture human moments through Wi-Fi and GPS devices. Then the question arises that how we can detect communities? In this paper we will be going to detect the communities from trajectories (it refer to the moving objects). The community detection is usually achieved by clustering. The objective of trajectory clustering is to identify cluster from a set of trajectory of moving objects ^{[1][2]}. Some of the examples of trajectory data are human behavior tracking, animal movements, vehicle positions and many more. We are inspired by some of real time use cases such as:

Social Recommendation: When a group of people visits a mall or browsing center they will recommend a new products or sites for their purchase and they will be inform about the new offers.

Online and offline behavior analysis: By merging knowledge of the people who communicate with their social media with the people who communicate physically, by using these knowledge social scientists will be able to create adaptable methodologies of human social interaction.

In this paper we will be going to identify group of objects from trajectory based on some behavior and movements. The main difference between clustering and community is, clustering contains group of objects and communities is the collection of clustering.

II. RELATED WORKS

2.1 Multifeature object trajectory clustering for video analysis: In these paper based on the behavior of the peoples we will calculate the sample patterns. It mainly consists of three steps namely: in the first step we will extract the trajectory features spaces; in next step we will extract the adjacent clusters and in the last step based on these details we apply the merging procedure which helps to merge the common adjacent clusters. This algorithm is evaluated based on the standard data sets and compared with state of art techniques. By using this method we can discover the common pattern in videos.

2.2 Making recommendations from multiple domains: Now a day the large amount of data has been available in the World Wide Web, a recommender system is being used to filter the important information that would help the users. Traditional systems suggest based on the single domain such as movie and book domain. Current work has tested the interrelations in different domains and designed models that exploit the user preferences. However, these methods are based on matrix factorization and can only be applied to two-dimensional data. Transferring high dimensional data from one domain to another requires decomposing the high dimensional data to binary relations which results in information loss.

2.3 The effect of context aware recommendations on customer purchasing behavior and trust: In particular, we did live controlled experiments with real customers of a major commercial Italian retailer in which we compared the customers' purchasing behavior and measured their trust in the provided recommendations across the contextual, content-based and random

recommendations. As a part of this study, we have investigated the role of accuracy and diversity of recommendations on customers' behavior and their trust in the provided recommendations for the three types of RSEs. We have demonstrated that the context-aware RS outperformed the other two RSEs in terms of accuracy, trust and other economics-based performance metrics across most of our experimental settings.

III. SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

These are some of the drawbacks in the existing system:

Previously trajectory clustering is completely based on a single information source such as user location data^{[3] [2]}; due to these community relationship and real world relationship will be missing and results will be false identified. And due to these multiple information sources will be not considered.

Communities are usually identified over a link based graph which captures only pair wise communication^{[4] [5] [6]}. Such communication details are not promising and such details has technical limitation and identification of communities are misleading.

We can able to measure the edges in the pair wise connection but measuring the communities within that connection will be difficult and it is difficult to categorize the incorporate additional similarity metrics.

3.2 PROPOSED SYSTEM

In this paper, we will discover communities from trajectories, which main intension is to identify group of objects from the trajectory data set. Our main approach is to measure the behavior of multi-source scattered process and combining the different dimensions into a single multi-attribute weighted combination. In early approach we will be forming a community based on single information source, such as location data, but here we will be considering the multi-information source and then we will form a community. The peoples who are present within this community can be able to share and gather the information related to social recommendation and online/offline behavior analysis.

Our project mainly consists of user, admin phase, general recommendation and recommendation.

Admin: Administrator has the responsibility of ensuring that the administrative activities within an organization run efficiently, by providing structure to other employees throughout the organization. These activities can range from being responsible for the management of human resources, budgets and records, to undertaking the role of supervising other customer. These responsibilities can vary depending on the customer and level of education. His main role is to control the overall operations. Whenever a new person wants to join for community then he will send the request to the admin by filling up the registration form. Based on these personal details admin will add him to the community and he will post some of the information which helps the user.

User: A user is a person who uses a computer or network service. Users generally use a system or a software product without the technical expertise required to fully understand it. **Power users** use advanced features of programs, though they are not necessarily capable of computer programming and system administration. When users are authenticated from the admin, based on the username and password they can able to login, and will be allowed to communicate with each others. The users are allowed to post the information to the other users. If he is interested in others, he can able to send the request to them. Mainly when he wants some suggestions from the others, then he can be able to obtain the details. Examples: If the user wants to purchase any dresses, but he don't have any idea about where to buy them and in which shop the discounts are there and then based on the user trajectory data he can able to get the information's easily.

Recommendation: In this module, we develop the estimation of query resolution probabilities. So far we have assumed that resolution probabilities for queries of different types are known. In practice they can be easily estimated. In order to ensure unbiased estimates can be obtained at each node, suppose a small fraction of all queries is marked 'RW', forwarded via the random walk policy with a large TTL, and given scheduling priority over other queries.

General Recommendation: In this general recommendation, a group of customers stay longer, visit more stores and spend more money than a single customer, and while the mixed groups (male and female together) stay for a shorter duration, they spend more money and visit more stores. Clearly, these preliminary results provide evidence that mobile advertisements should be carefully targeted to differentiate between individuals and groups (and different group types).

3.3 SYSTEM ARCHITECTURE

Figure 1.1 shows the system architecture which consists of mainly three distinct phases:

- In the first phase based on the trajectory data we will calculate four distinct dimensions, namely:

Semantic kernel: It contains the information about the sequential sites within the trajectory. Consider the example that, if we have N distinct site, then the each trajectory can be specified by site transition sequence with corresponding sensual intervals.

Example: If the user is moving from source A to destination D, then he needs to pass through the different sites and he may pass in different directions(A->B->C->D or A->C->B->D), these all information will be monitored and based on these results the group will be formed and will represented as K1.

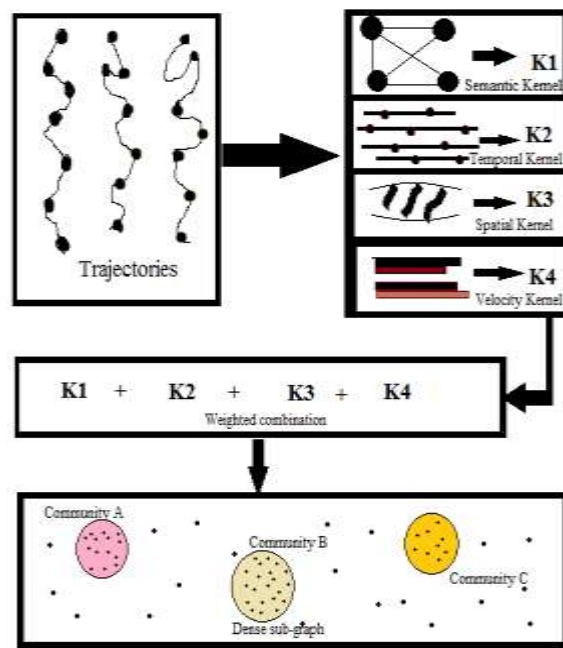


Figure 1.1: System Architecture

Temporal kernel: It contains the information about the amount of time the people will spend. If we consider the example of shopping mall, there we will obtain the temporal data based on the amount of time the customer spent in a specific shop.

Example: Consider the user A, if he is rooming inside the shopping mall, then if he saw any interested thing then he will stop at that point and he will spend some amount of time there, incase if he is not interested in anything he may move out quickly. These results will be combined and the obtain results will be named as K2.

Spatial kernel: Spatial data is nothing but the earth data, which consists of the location details. It is used to measure the spatial similarity among the individual trajectories. We can use the global alignment kernel to measure the closeness among the trajectories.

Example: Consider the users called A and B, if they travelling, then the spatial similarities between the user A and user B will be calculated and the obtained results will be considered as result K3.

Velocity kernel: It is measured based on the velocity of the moving objects. For example if we take a group of peoples who are moving, then based on the movement the peoples will be classified. That means people who are moving slow will be categorized into one group, and people who are moving fast will be categorized into another group.

Example: Consider the user A, if he is travelling from source S to destination D, then the amount of time he is taking to reach the destination will be monitored, that is based on whether the user is moving fast or whether he is moving slow will be considered and the results will be stored in K4.

Above 4 similarities are compute by applying proper kernels for each dimension to extract the key relevant features.

- In the second phase we will combine all these similarities based on weight and multi-modal diffusion process and based on these results the trajectory community discovery will be performed. ($K1+K2+K3+K4$)

- In the last phase we use the dense sub-graphs detection method to detect the highly connected sub-graph from the graph. Based on these trajectory communities will be detected from similarity values.

IV. CONCLUSION

In this paper we recommend trajectory community for a multi-source scattered modeling. Our main approach is to measure the behavior of multi-source scattered process and combine the different dimension into a single multi-attribute weighted combination. The community detection is usually achieved by clustering. The objective of trajectory clustering is to identify cluster from a set of trajectory of moving objects Experiments were conducted on real life datasets like: customer in a shopping mall, students present in a campus building and cab drivers in a city. The results indicate that our user recommendation method detects the correct groups and sends the information to target from different trajectory data.

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