Inferring Distant-Time Location in Low-Sampling-Rate Trajectories

Meng-Fen Chiang[§], Yung-Hsiang Lin[§], Wen-Chih Peng[§] and Philip S. Yu [†]
[§]Department of Computer Science, National Chiao Tung University, Hsinchu, Taiwan
[†]Department of Computer Science, University of Illinois at Chicago, Chicago, Illinois, USA
[§]{ mfchiang.cs95g,shiang1095.cs00g,wcpeng}@nctu.edu.tw, [†] psyu@cs.uic.edu

ABSTRACT

With the growth of location-based services and social services, low-sampling-rate trajectories from check-in data or photos with geo-tag information becomes ubiquitous. In general, most detailed moving information in low-sampling-rate trajectories are lost. Prior works have elaborated on distant-time location prediction in high-sampling-rate trajectories. However, existing prediction models are pattern-based and thus not applicable due to the sparsity of data points in low-sampling-rate trajectories. To address the sparsity in low-sampling-rate trajectories, we develop a Reachability-based prediction model on Time-constrained Mobility Graph (RTMG) to predict locations for distant-time queries. Specifically, we design an adaptive temporal exploration approach to extract effective supporting trajectories that are temporally close to the query time. Based on the supporting trajectories, a Time-constrained mobility Graph (TG) is constructed to capture mobility information at the given query time. In light of TG, we further derive the reachability probabilities among locations in TG. Thus, a location with maximum reachability from the current location among all possible locations in supporting trajectories is considered as the prediction result. To efficiently process queries, we proposed the index structure Sorted Interval-Tree (SOIT) to organize location records. Extensive experiments with real data demonstrated the effectiveness and efficiency of RTMG. First, RTMG with adaptive temporal exploration significantly outperforms the existing pattern-based prediction model HPM [2] over varying data sparsity in terms of higher accuracy and higher coverage. Also, the proposed index structure SOIT can efficiently speedup RTMG in large-scale trajectory dataset. In the future, we could extend RTMG by considering more factors (e.g., staying durations in locations, application usages in smart phones) to further improve the prediction accuracy.

Categories and Subject Descriptors

H.3.1 [**Information Storage and Retrieval**]; H.5.2 [**Information Interfaces and Presentation**]

General Terms

Algorithms, Design, Human Factors

KDD'13, August 11–14, 2013, Chicago, Illinois, USA.

Keywords

Location Prediction, Sparsity, Reachability

1. INTRODUCTION

With the growth of location-aware technologies and location based Internet services (e.g., Foursquare and Places on Facebook), tracking or collecting a huge amount of trajectories of users becomes feasible. Given a set of trajectories, prior work in [2] has formulated a distant-time query, where given a query time, the current location and time, an estimate location of moving objects at the query time is returned. The distant-time query is useful in many applications, such as content-based delivery networks, inferring regions for tourism recommendations, and estimating the traffic status for transportation management [7].

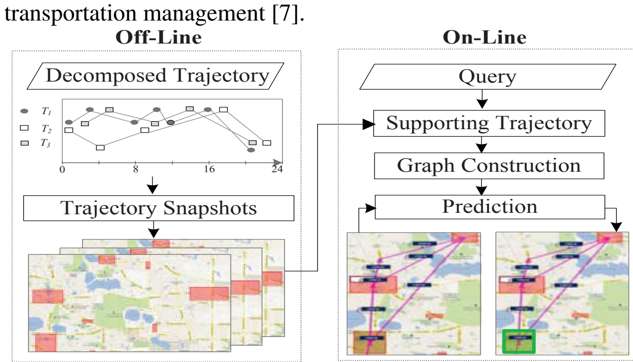


Figure 1: Framework Overview

Time-ordered check-in records of a user becomes ubiquitous as users could easily perform check-in services (e.g., Foursquare) to note their locations with a mobile phone or people can share geo-tagged photos whose time-stamps and geo-locations on a photo sharing website (e.g., Flickr). Without loss of generality, the time-ordered check-in records of a user are able to be expressed as low-sampling-rate trajectories, where details of movement information are lost [8]. A considerable amount of efforts has been devoted to design location prediction models [2, 5, 3]. For example, the authors in [5] proposed a location prediction model to infers next location of a user based on collective frequent patterns discovered from previous trajectories of all users. However, [5] fails to predict distant-time future locations. A hybrid prediction model (HPM) in [2] partially address the problem of answering distant-time future locations. HPM relies on frequent moving patterns discovered from past trajectories as well as existing motion functions using the objectąęs recent movements to support future location queries. While pattern-based prediction models over high-sampling-rate trajectory databases show promising query results, it fails to effectively predict distant-time location queries over low-sampling-rate trajectories in terms of both coverage and accuracy because HPM can fail to discover frequent moving patterns due to data sparsity.

In this paper, we address the sparsity issue in low-sampling-rate trajectories for distant-time query. Specifically, given current location at the current time point and a query time, we aim to predict the location of a user at query time. We present a Reachability-based prediction model on Time-constrained Mobility Graph (abbreviated as RTMG) that investigates user's reachability and determines the possible candidate locations. Given a query, the core components in RTMG are as follows:

- **Adaptive Supporting Trajectory Retrieval**: By expanding investigation time interval between current time and query time, we can infer paths from region A to other regions within the investigation time interval. These trajectories are called supporting trajectories.

- **Time-Constrained Mobility Graph**: Based on the supporting trajectories, a Time-constrained mobility Graph (abbreviated as TG) that captures a user's moving behavior within a time interval is constructed.

- **Reachability Probabilities**: In light of TG, we derive reachability probabilities of vertexes (i.e., the locations) in TG and thus determine the most likely location at the query time.

2. FRAMEWORK OVERVIEW

RTMG consists of two phases, off-line trajectory pre-processing and on-line location prediction as shown in Figure 1. The following subsections briefly describe how each module works.

2.1 Off-Line: Trajectory Pre-processing

Derive Trajectory Snapshots: In off-line phase, we derive *a sequence of trajectory snapshots* from raw trajectories to better capture the spatial and temporal correlations. Formally, given a trajectory database $\mathbb{T}^d$ of equal time interval (e.g., a day) and a time cell size δ_t, a sequence of trajectory snapshots $\mathbb{C}(\delta_t, \mathcal{L})$=$\{C_1, ..., C_n\}$ is obtained by partitioning the trajectory database in temporal dimension into n time cells of equal size (i.e., $n \cdot \delta_t = d$) and transforming location records into region symbols $\mathcal{L}$ discovered from original location records. Figure 3 illustrates an example of trajectory snapshot in daily scale and the location information of records is represented by region identifications. For example, trajectory T_1 consists of six location records $\langle g_{1,1}, ..., g_{1,6}\rangle$. Snapshot C_2 consists of two regions C and D.

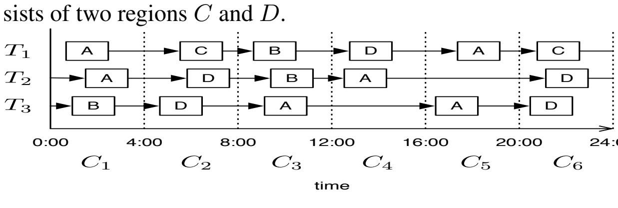


Figure 3: Trajectory database

Data-centric Index Structure: To improve efficiency of query processing, we design an index structure, Sorted Interval-Tree (SOIT), to structure user mobilities according to their time locality into a data-centric balanced tree. Several operators are defined to efficiently retrieve supporting trajectories and infer time-constrained mobility network on-the-fly. SOIT indexes a set of location records into a balanced tree such that each leaf time cell contains similar amount of data by partitioning a timeline into a sequence of time cells and maintaining a set of location records in each time cell no more than the size of b, where b is the branching factor. Figure 4 illustrates a set of location records indexed by SOIT with a branching factor of three. Centered at $Q.ct$=5am, the partitions that overlap with the time point is N_{12}, which consists of three location records, one locates at location C and the other two locate at location D.

Each leaf time cell of SOIT is associated with a group of inverted files, where each inverted file stores a group of location records with their time-stamps covered by the leaf time cell. Each record in an inverted file that is covered by time cell N contains four entries: (1) Now: location record covered by N, (2) Next: location record immediately after Now, (3) TD: travel time between the end time of Now and the start time of Next and (4) SD: total time that a user stayed during Next. All leaf time cells are sorted according their start time in ascending order and are connected into a list with sibling link for efficient query processing.

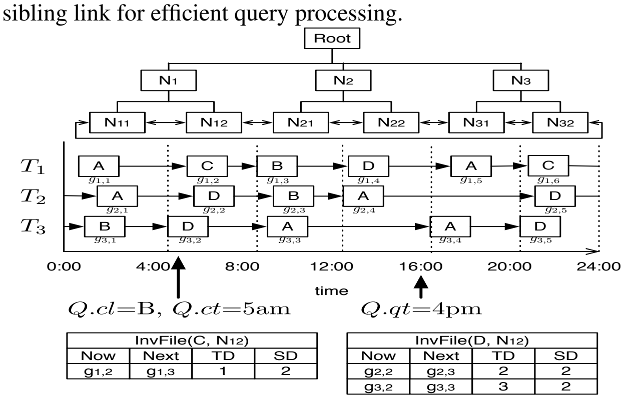


Figure 4: Indexing scheme and query processing

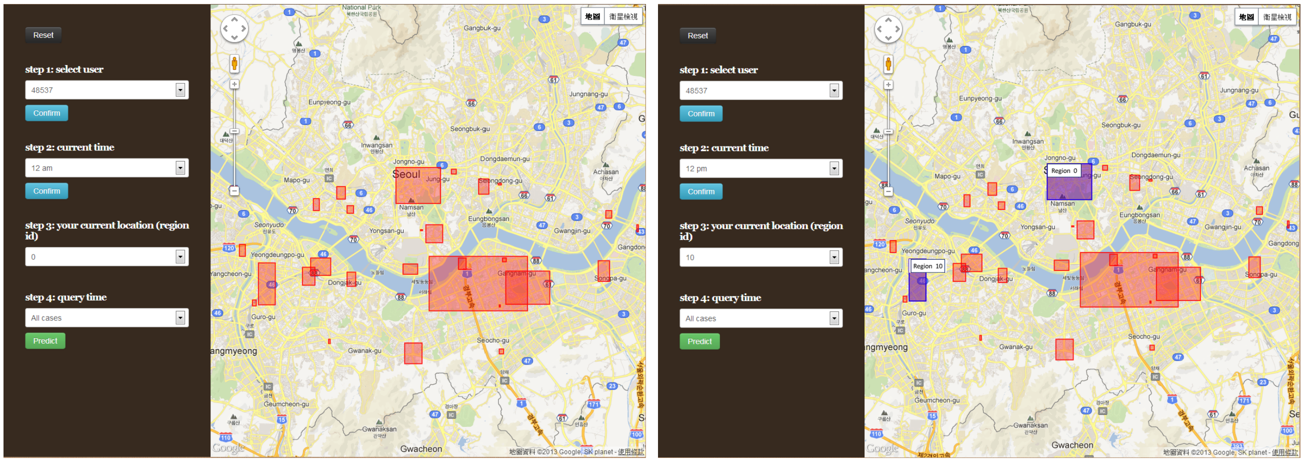
SOIT facilitates efficient retrieval of time cells based on their temporal locality. To achieve this, we modify the general insertion procedure of building a balanced R-tree by grouping and ordering time intervals according to their start points. The idea of finding a time cell that an incoming location record should be inserted is as follows. If the time cell has enough space, then the location record is inserted to the time cell. Otherwise the time cell is split into two. Let g denote a location record to be inserted. If the minimum bounding time interval of an entry e in a time cell contains the start time of g, we can place g in entry e in ascending order of their start times. Then we follow the pointer of the current entry. Recursively, we continue this procedure until a leaf time cell is reached.

2.2 On-Line: Location Prediction

Adaptive Supporting Trajectory Retrieval: Adaptive temporal exploration aims to dynamically determine the time interval for a query based on the temporal correlation between the query and current set of supporting trajectories. We invoke adaptive temporal exploration if we do no have sufficient and high quality supporting trajectories to develops the prediction model for a given query. Specifically, if we do not have sufficient supporting trajectories in the desired time interval, we broaden the time interval with the guidance of temporal correlation between the query and current set of supporting trajectories. Otherwise, we accomplish the extraction of supporting trajectories in the desired time interval. If the entire timeline is investigated, essentially the whole set of trajectories is used to provide more information, and thus may be more useful.

When the entire timeline is investigated (i.e., full exploration with $k = \frac{n}{2}$), essentially the entire set of trajectories will be considered as the set of supporting trajectories, where n is the number of snapshots.

Time-Constrained Mobility Graph: Inspired from the previous work [3], we model user mobility behavior as a Time-constrained



(a) All Regions

(b) Time-Constrained Regions

Figure 2: Screenshots of region investigation: (a) frequently vistaed regions; (b) frequently vistaed regions constrained on a temporal condition (i.e., current time)

mobility Graph (abbreviated as TG). TG is represented as a directed weighted graph $\mathbb{TG}^Q$=(V,E,W), where each node $v \in V$ represents a location and each edge $e(u,v)$ represents a transition from location u to location v weighted by transition frequencies denoted $w(u,v)$. TG is built from the set of supporting trajectories. Explicitly, for each supporting trajectory $S_{i,j,k}$, the set of unique locations in $S_{i,j,k}$ forms V. A path from the location associated with location record j to the location associated with location record k is created and the transition probability associated with an edge $e(u,v)$ is updated accordingly. Consequently, from the set of supporting trajectories, TG is able to capture movement behaviors during the time interval [$Q.ct$, $Q.qt$].

Reachability Probabilities: Most previous studies evaluated the possibility of a candidate location merely according to mobility statistics such as immediate transition probabilities of moving patterns [2] or the traveling probability of a path [3]. For example, given a candidate path P: $v_1 \rightarrow ... \rightarrow v_k$ up to a prediction length, MaxLike in [3] returned the path v_k as the predicted answer if the travel probability of the path P is maximized among all possible paths between v_1 and v_k.

The mobility statistics collected from low-sampling-rate trajectories are very sparse and making prediction merely based on sparse mobility statistics of a single transition or a single path derived from a mobility graph may bias the prediction results. In addition, rather than probabilities of single immediate transition or single path, the probability of connectivity between node pairs is an important indicator of closeness of the node pair. Some node pairs that are located structurally close to each other in a time-constrained mobility graph and can be easily identified based on simple mobility statistics, e.g., immediate transition probability.

To incorporate both immediate transition frequency and connectivity in distant-time location prediction, we use the metric, reachability RCH, to estimate the probability that a user is located at each candidate region on a TG.

Definition (Reachability) Let A be the $|V| \times |V|$ transition probability matrix of a time-constrained mobility graph TG $\mathbb{G}^Q$. Given the restart probability c ∈(0,1), the reachability from $Q.cl$ to any node $v \in V$ is denoted as a vector $RCH_{Q.cl}$. $RCH_{Q.cl}$ can be derived by

$$RCH^k_{Q.cl} = cE_{Q.cl} + (1-c)RCH^{k-1}_{Q.cl}A \qquad (1)$$

when $RCH_{Q.cl}$ is converged, where $E_{Q.cl}$ is a vector, the entry representing $Q.cl$ is one and the rest entries are set to be zero.

Given a query Q and its TG G^Q, we propose to compute the reachability between $Q.cl$ and $v \in V$ in G^Q as a metric to predict the user's location at query time $Q.qt$.

3. DEMONSTRATION PLAN

3.1 Demonstration Settings

We utilize Gowalla dataset to verify our prediction model. The dataset contains 50 users, 113 decomposed trajectories in daily-scale, and 30 distinct user-specific regions on average. The average time interval between consecutive location records is approximately 17 days. The regions were discovered by OPTICS [1] with ε set to be 100 meters and $MinPts$ set to be three.

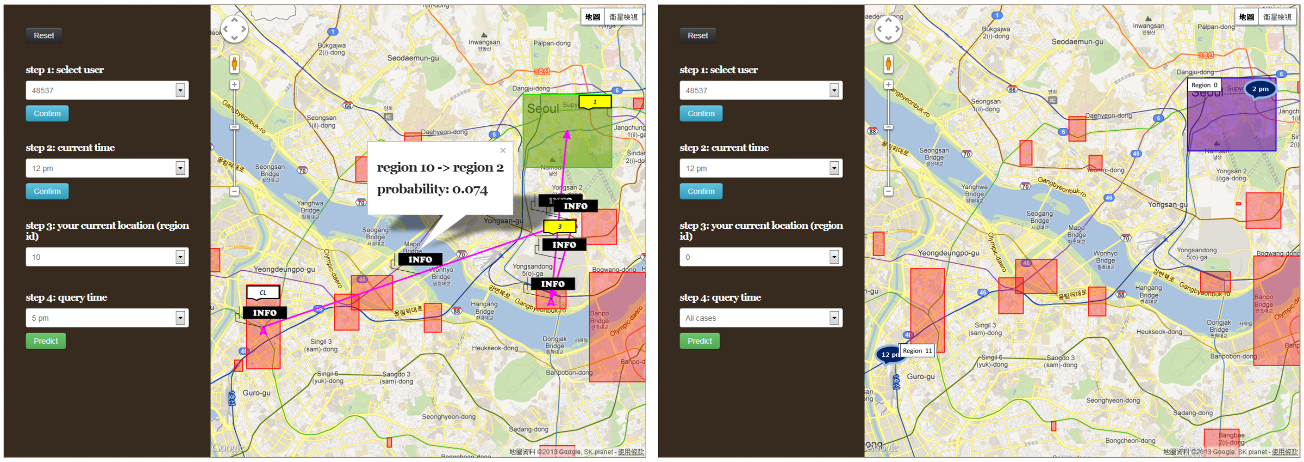
3.2 Demonstration Scenarios

From this interactive interface [1], users can format several queries to investigate particular user's movement behavior and visualize future locations at query time. We describe each of them as follows:

Show frequently visited regions: To visualize user's frequently visited regions, we can format a query by selecting a user ID, each frequently visited region will be expressed as a red-colored rectangle shown on the map. The set of regions are derived by OPTICS algorithm which is widely used to mines dense regions from a sequence of location points. For example, Figure 2a shows the set of frequently visited regions of the user (ID=48537).

Show time-constrained regions: To visualize frequently visited regions constrained at a timepoint of interest, we can format a query by selecting a user ID and the timepoint of interest. The set of regions visited at specified timepoint will displayed as purple regions. This helps us to investigate the correlation between time and locations. For example, Figure 2b illustrates two purple regions (Region 0 and Region 10) correlated with the timepoint 12pm for the user (ID=48537).

[1] http://carweb.cs.nctu.edu.tw/ shiang/DTLP2/index.html



(a) One Query Time

(b) All Query Times

Figure 5: Screenshots of two typical location prediction: (a) future locations at possible query times; (b) top-k future locations at specified query time and its time-constrained mobility graph

Following this, we implement two functionalities to visualize location prediction results as shown in Figure 5.

Future location at specified query time and its time-constrained mobility graph: Given the user ID, a current location, a current time, and a query time, this functionality shows the top-3 future locations with maximum reachabilities at specified query time, where a region attached with a white label *CL* is the user's current location, a yellow tag with a ranking number is attached to returned locations and the actual location at the query time (i.e., ground truth) is displayed as a green region. For example, given user ID to 48537, current time 12pm at region 0, specifying query time at 5pm and pressing prediction button, the system returns top-3 candidate locations at 5pm with a yellow tag indicating their rank as illustrated in Figure 5a. In this case, the actual location at 5pm (expressed as green region) is also the top-1 predicted location.

Additionally, we also illustrate the time-constrained mobility graph connecting historical traversed regions between the current time and the query time, where nodes represent regions and edges represent the transition probabilities between two regions. As illustrated in Figure 5a, it shows the mobility graph with four nodes and three edges, where the transition probability from one region to another is recorded in INFO icon. For example, the INFO shows that the transition probability from region 10 to region 2 is 0.074.

Future location at all possible query time: Given the user ID, a current location, a current time, this functionality shows all future locations at all possible query time. As shown in 5b, given user ID to 48537, current time 12pm at region 0, selecting all cases at step 4 and pressing prediction button, the system will return all possible locations at varying query times. In this case, two possible locations (region 0 at 2pm and region 11 at 12pm) are returned and displayed in purple-colored rectangles on the map.

4. FURTHER DISCUSSION

To address the sparsity in low-sampling-rate trajectories, we develop a Reachability-based prediction model on Time-constrained Mobility Graph (RTMG) to predict locations for distant-time queries. The prototype of Reachability-based prediction model we implemented can be applied to many different scenarios, including urban planning[4], location recommendation or even location-based content delivery networks (e.g., coupons) [6] by incorporating user's future location as a feature to intelligently deliver spatio-temporal sensitive information.

5. REFERENCES

[1] M. Ankerst, M. Breunig, H. Kriegel, and J. Sander. Optics: ordering points to identify the clustering structure. *ACM SIGMOD Record*, 28(2):49–60, 1999.

[2] H. Jeung, Q. Liu, H. Shen, and X. Zhou. A hybrid prediction model for moving objects. In *Proceedings of the 24th ICDE International Conference on Data Engineering*, pages 70–79. Ieee, 2008.

[3] H. Jeung, M. L. Yiu, X. Zhou, and C. S. Jensen. Path prediction and predictive range querying in road network databases. *The VLDB Journal*, 19:585–602, August 2010.

[4] V. Lakshmanan. *Automating the Analysis of Spatial Grids: A Practical Guide to Data Mining Geospatial Images for Human & Environmental Applications*. Springer Publishing Company, Incorporated, 2012.

[5] A. Monreale, F. Pinelli, R. Trasarti, and F. Giannotti. Wherenext: a location predictor on trajectory pattern mining. In *Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pages 637–646. ACM, 2009.

[6] V. Sourlas, G. S. Paschos, P. Flegkas, and L. Tassiulas. Mobility support through caching in content-based publish/subscribe networks. In *Proc. of the Cluster 10th IEEE/ACM International Conference on Cloud and Grid Computing*, pages 715–720, 2010.

[7] J. Yuan, Y. Zheng, C. Zhang, W. Xie, X. Xie, G. Sun, and Y. Huang. T-drive: driving directions based on taxi trajectories. In *Proceedings of the 18th SIGSPATIAL International Conference on Advances in Geographic Information Systems*, pages 99–108. ACM, 2010.

[8] K. Zheng, Y. Zheng, X. Xie, and X. Zhou. Reducing uncertainty of low-sampling-rate trajectories. In *Proceedings of the 28th ICDE International Conference on Data Engineering*, pages 1144–1155. ICDE, 2012.