# 國立交通大學

## 資訊科學與工程研究所

## 碩士論文

基於歷史軌跡資料探勘相關停留區域

Mining Top-k Relevant Stay Regions

from Historical Trajectories

研究生：林詠翔

指導教授：彭文志 教授

中華民國 102 年 7 月

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# 基於歷史軌跡資料探勘相關停留區域

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## 摘要

隨著具有GPS定位功能的設備越來越廣泛的被使用，如：GPS定位器、智慧型手機及導航機，大量的軌跡資料可以被收集，並且使用者可以藉由上傳他們的軌跡資料以獲得基於地點的服務。預測使用者下一個可能停留的位置對使用者是很有幫助的，當這些相關停留區域被探勘出來，一些交通狀況、商家廣告、旅遊景點推薦等關於下一個停留位置的地點服務將可以被提供。先前關於位置預測的研究都是從整群的軌跡資料中發掘停留區域並找出區域與區域間的關係來描述使用者的移動模式。然而，我們認為軌跡資料即使經過相同的區域並不代表擁有相似的移動行為。

此論文中，我們提出一個系統架構來探勘關於特定移動行為的停留區域並且用於位置預測，包含兩個部分：Region Modeling以及Mobility Prediction。對於Region Modeling，我們提出軌跡分群法將相似形狀的軌跡分群，並且從分群的結果中發掘停留區域；對於Mobility Prediction，我們提出挑選軌跡群的演算法及預測策略來找出最佳k個相關停留區域。

我們利用了實際資料進行相關實驗，結果顯示我們的方法可以有效地預測停留位置，且準確度達到接近60%，而nDCG評估也可以達到80%。

Mining Top-k Relevant Stay Regions from Historical Trajectories

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## ABSTRACT

With increasingly prevalent mobile positioning devices, such as GPS loggers, smart phones, and GPS navigation devices, a huge amount of trajectories data is collected. Users are able to obtain the various location-based services by uploading their trajectories. Predicting the next region the user may possibly stay is very useful. Once a set of stay regions discovered, traffic status, targeted advertises, sightseeing recommendations, and other location-based information of the next stay can be provided in advance. Prior works have elaborated on discovering stay region from the whole crowd trajectories and then exploring the relations between the regions to describe the movement patterns for location prediction. However, the trajectories pass the same region may not have the similar movement behavior.

In this paper, we propose a framework to discover stay regions relevant to the specific movement behavior and then applied in location prediction, called Region Modeling and Mobility Prediction. The proposed framework includes two modules: region modeling and mobility prediction. In the region modeling module, we develop shape-clustering method to group the similar trajectories from historical data and then explore the stay region model from trajectory clusters. Based on the discovered region model, the mobility prediction module provide a cluster selection algorithm and several prediction strategies to generate the top-k relevant stay regions.

In an experimental evaluation, We evaluated the prediction method by using labeled ground truth. The experimental results show that the prediction accuracy of our method can reach 60% and nDCG is more than 80% .

# 誌謝

很高興於兩年前成為前瞻資料庫系統實驗室的新成員，而研究所的兩年生活倏忽即逝，在這段期間最想感謝的是我的指導教授彭文志老師，老師不僅在研究領域上不斷地給予我研究相關的專業知識，對於研究態度、人生方向以及做人處事更是時時地提醒我們、引導著我們。如此才能夠讓我順利地突破一切難題，完成碩士學位。

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最後，我要特別感謝長久以來家人的支持與陪伴。在各方面你們默默的支持我、包容我，讓我專心地將碩士研究完成。

# Contents

# List of Figures

# List of Tables

# Chapter 1

# Introduction

While the mobile positioning devices become prevalent, a tremendous amount of trajectory data are generated. Users can upload their trajectories or check-in data to location-aware web provider(e.g., @trip, Foursquare and Facebook) and obtain the various location-based services such as tourism recommendations and store advertising in their daily life. In general, trajectory data is a sequence of GPS points and these sequential GPS points record the users' true movement. If some similar trajectories frequently appear in a user's historical trajectory data, we are able to suppose that the user may have a certain movement behavior. However, due to the uncertainty of GPS position collected, it is difficult to discover that the trajectories are completely repeated. For example, in figure 1.1, there are three historical trajectories of one user in different days with different colors. These trajectories are not completely the same but pass through same specific stay regions. This observation shows the user usually take similar routes. Those trajectories have similar shape and pass through some specific stay regions together. Thus, we claim that a user's movement behavior can be discovered by clustering the trajectories with the similar shape and then resulted in some stay regions where the user frequently passed. Such stay regions are able to bring many applications such as inferring regions for sightseeing and tourism recommendations and estimating the traffic status for transportation management [1]. Once a set of stay regions discovered, lots of information could be provided to user, such as coupons of stores near by stay location, traffic status on the way to destination, and even the next possible stay region also can be obtained so that it is useful for navigation system to set the destination automatically. In this paper, we focus on the problem of mining stay regions from historical trajectories and applied in location prediction problem.

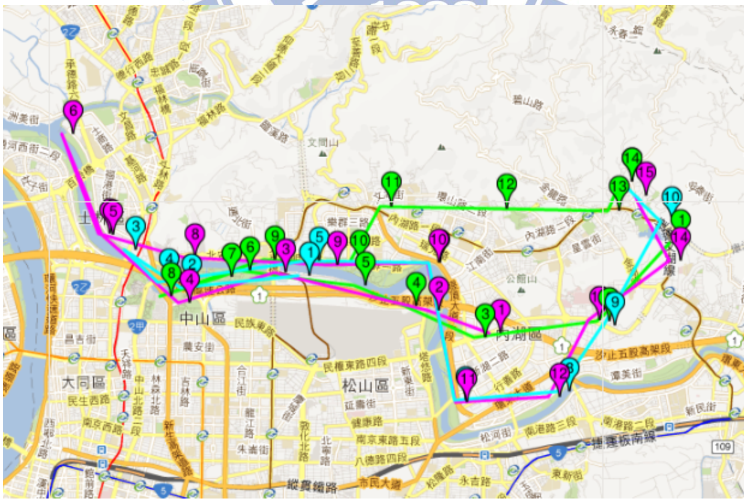


Figure 1.1: An example of the similar-shape historical trajectories.

Given a set of trajectories, prior works have studied the location prediction problem in which given the users current location, the problem is to predict the next location or the location at a specific time. In [2], the authors proposed to split the map or trajectories into a set of regions and use historical trajectories to estimate the transition probability between each region. Then, according to the user's current location for prediction. The authors in [3, 4] construct a decision tree according to trajectories and use tree structure to denote the stay locations for prediction. These existing research works focus on discovering stay region from the whole crowd trajectories and then exploring the relations between the regions to describe the movement patterns for location prediction. However, the trajectories pass the same region may not have the similar movement behavior. For instance, we may stay a restaurant for lunch and stay the same region for exercise at night because there may be a park in the same region. In this paper, the stay region detection is generated from the group of trajectories with the similar movement behavior and then applied for improving the destination prediction. The advantage of predicting the future location by the stay regions generated from the similar movement behavior is that the regions where the user frequently stay are the same even if the user detours. For example, Figure 1.2 shows a user's historical trajectories such as going to work from home at about 8:10 in the morning, getting off work from office at about 17:15 and buying his/her dinner on the way to home, and jogging around park after dinner. Suppose the user is in the restaurant and current time is 17:40, then we can surmise the movement behavior of the user is going home from office and the future stay region relevant to this behavior is home.

In this paper, we propose a framework to discover stay regions relevant to the specific movement behavior and then applied in location prediction, called **Region Modeling and Mobility Prediction**. Specifically, the framework includes two models: **Region Modeling Module** and **Mobility Predic-**

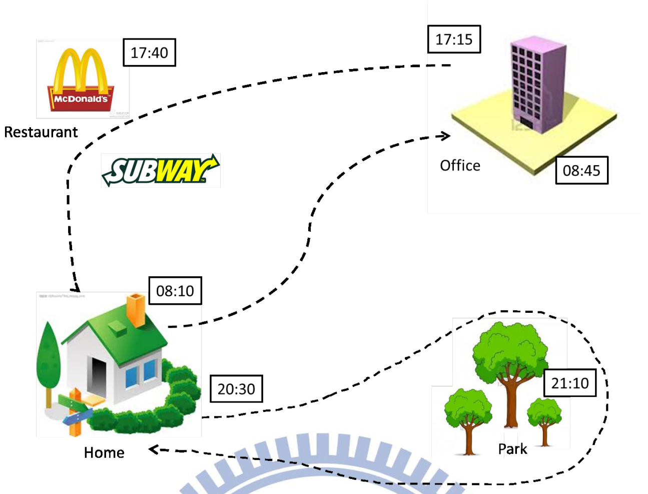


Figure 1.2: An example of the historical trajectories with movement behavior

**tion**. In **Region Modeling Module**. Given a use's individual trajectory data, in region modeling, we develop the shape clustering method to group the trajectories with the similar movement shape to discover the user's movement behavior and then a set of trajectory clusters is generated. Based on the trajectory clusters, a stay regions model is discovered for each trajectory cluster. In mobility prediction, given the starting location and current time, top-k stay regions relevant to the user's movement behavior will be provided. We design an algorithm to select trajectory cluster, i.e. the movement behavior, by considering the user's starting location and current time. Then, several prediction strategies are proposed to generate top-k stay regions relevant to the user's movement behavior. We evaluate the performance of our system by real-world dataset generated by users in a period of four months in Taiwan. In addition, we also compare our framework with the existing approaches and extensive experiments are conducted to demonstrate the effectiveness of our framework.

The contributions of this study are:

1) We predict top-k relevant stay regions for users from his/her historical trajectories. The result can be used on trip recommendation and navigation systems.

2) We study that movement behavior can be mined from similar-shape trajectories.

3) In the prediction module, the three score functions are adopted to obtain the top-k relevant stay regions, and consider time difference, location distance and frequency respectively.

4) We conduct a comprehensive performance evaluation. The experimental results show that both the precision and nDCG in our method can reach to 70%.

The rest of this study is organized as follow: Section 2 defines the terms and notations used in this paper and gives a overview of our approach in this paper. Section 3 describes algorithms: trajectory clustering, stay points detection and stay region clustering. Section 4 describes prediction module for stay regions prediction. Performance studies are presented in Section 5. Section 6 introduces the current research works of the location and destination prediction system. Finally, Section 7 concludes this paper.

# Chapter 2

# Problem Statement and Framework

In this section, we present an overview of our design. Section 2.1 formally presents the problem statement. Section 2.2 presents the framework in this paper, which is comprised of two components: **Region Modeling Module** and **Mobility Prediction**.

## 2.1 Problem Statement

We develop a trajectory clustering algorithm in our framework. Given a set of *trajectories* $Trajs = \{T_1, T_2, ..., T_{num_{tra}}\}$, our algorithm generates a set of *trajectory clusters* $TClusters = \{TC_1, TC_2, ..., TC_{num_{tc}}\}$. For every *trajectory*, there are some *stay points* that user stayed in the past. All of *trajectories* in the same *trajectory cluster* can consist of some *stay regions* or *relevant stay regions* formed by *stay points*. The *trajectory*, *trajectory* *cluster*, *stay point*, *stay region* and *relevant stay region* are define as follows.

**Definition 1** ***(Trajectory)*** *A trajectory is a sequence of GPS points. It is defined as* $T_i = p_1p_2p_3...p_j...p_{len_i}$ $(1 \leq i \leq num_{tra})$. *Here,* $p_j(1 \leq j \leq len_i)$ *is a 2-dimensional point which has a own precise location(latitude, longitude) and a timestamp. The length* $len_i$ *of a trajectory can be different from those of other trajectories.*

**Definition 2** ***(Trajectory Cluster)*** *A trajectory cluster TC is a set of trajectories. In this paper, The trajectories that belongs to the same cluster are close to each other according to the shape measure. In other word, the shape of trajectory is similar to the shape of each other in the same cluster.*

**Definition 3** ***(Stay Point)*** *A stay point SP in this paper should have one of the following two characteristics: 1) the location is where user stay for a while, or 2) where user walk around. In other words, a stay point contains some GPS points which are near by each other and their timestamp shows that the user stay for a long time. In Figure 2.1, there is a possible stay point in the trajectory. Under the premise of the GPS points have the sequential feature, we identify the location(mentioned as red area in Figure 2.1) is a stay point, because the distance between GPS point A and GPS point B is less than 500 meters and time difference between point A and point B is larger than 15 mins.*

**Definition 4** ***(Stay Region)*** *A stay region is represented by a set of stay points. It is defined as* $SR = \{sp_1, sp_2, ..., sp_{num_{sp}}\}$. *As the Figure 2.2, it is*

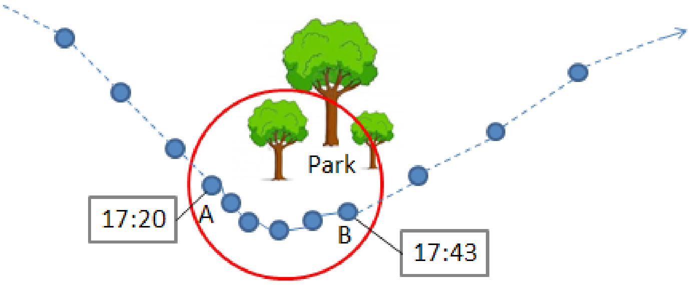


Figure 2.1: A trajectory with stay point

*an example of a stay region which shows that the coverage of stay points from the same trajectory cluster is the stay region.*

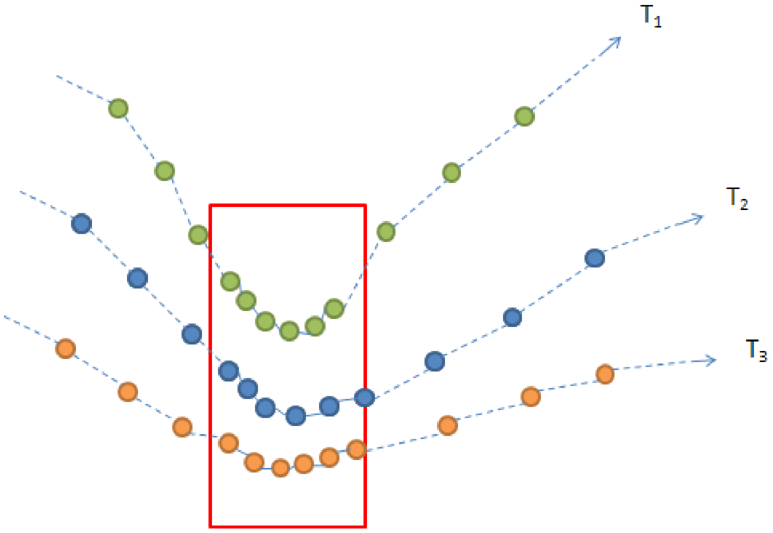


Figure 2.2: An Example of Stay Region

**Definition 5** ***(Relevant Stay Region)*** *A relevant stay region must follow a constraint that the time and location of stay region is related to query time and query location.*

We claim that the users' stay regions will be relevant movement behavior. In Fig. 1.1, we can observe that users' behavior is always regular. For instance, people often take the similar route from home to office at morning and take the similar route from office to home. Even doing sports such as jogging or mountain climbing also take the similar route. Therefore, these behaviors correspond their relevant stay regions because regular routes pass through some specific stay regions several times. In fact, relevant stay region is relevant with not only movement behavior but also starting location and time.

## 2.2 Framework

After description of problem statement, we describe the overview of this paper. Figure 2.3 shows the architecture of our system, which is comprised of two components: **Region Modeling Module** and **Mobility Prediction**.

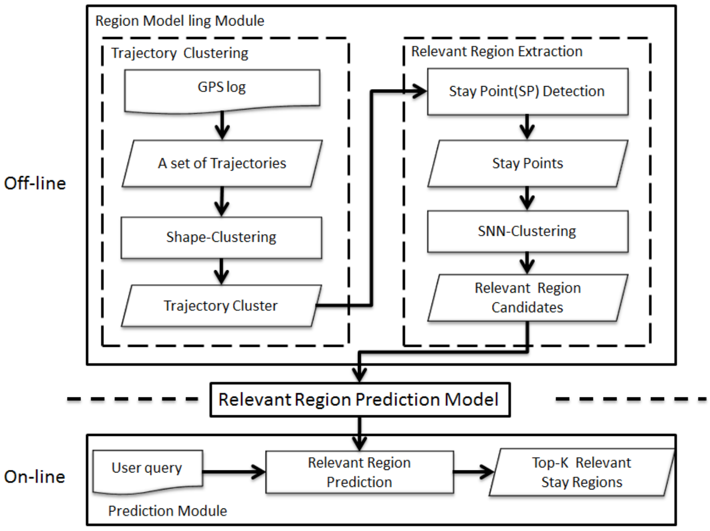


Figure 2.3: Framework

### 2.2.1 Region Modeling Module

In the first module, we adopt a clustering method called shape-clustering and aim to group the similar-shape trajectories since the stay points in each non-similar-shape trajectories have different meaning. Then detect stay points by using existing method. After detecting step, we adopt a Share Nearest Neighbor clustering(SNN-clustering) to cluster the stay points as stay regions. Finally, this module generates some relevant stay region candidates in each trajectory cluster.

### 2.2.2 Mobility Prediction

In the second module, we score the trajectory cluster according to query time and query location. After scoring the trajectory cluster, we design another score functions to rank the relevant stay region candidates from each trajectory cluster. After Considering the score of trajectory cluster and score of stay region candidate, the result of this module are top-k relevant stay regions with top-k score.

# Chapter 3

# Shape-Clustering and Region Modeling

In this chapter, we describe the **Region Modeling Module** which consists of two components: **Shape-Clustering** and **Region Modeling**. We proposed a trajectory clustering called **Shape-Clustering** to cluster the similar-shape trajectories. In **Region Modeling**, it decides the possible stay points in each trajectory cluster by using existing method after shape-clustering and cluster these stay points as relevant stay region candidates for prediction.

## 3.1 Shape-Clustering

In this section, we attempt to cluster the similar-shape trajectories. In Fig. 1.2, users' often take a regular route in daily life. We thought the similar-shape trajectories imply the same movement behavior. And according to the same behavior, there should exist fixed stay points on the route.

In existing work, a shape-based pattern detection method has been used to detect streaming time series data [5]. We consider that the same concept can be adopted on trajectory since we would like to find out the similar-shape trajectory. As shown in the Fig. 3.1, there are two trajectories $T_i$ and $T_j$ denoted as sequential GPS poins. Then, we define $segment_{i,n}$ as a $n$th trajectory segment in $T_i$ and the length of time interval is 25 seconds. And each segment has a 15 seconds overlap with its last segment. We calculate the average position(the two red points) in each segment according to latitude and longitude of GPS points in a segment. From the front of two trajectories, calculate distance $d$ defined as distance between the two average position(the two red points). As the algorithm 1, if the distance $d$ less than the distance threshold $\delta$, these two segments are considered as similar segments. In addition, we define a similar counter mentioned as $SimSeg$ in algorithm to count number of similar segments. Thus, the value of similar counter can be considered as similarity between two trajectories. Then, each two trajectories whose similarity is higher than similarity threshold $SimThres$ should be group into the same cluster. Otherwise, the trajectory form a new cluster independently.

## 3.2 Region Modeling

In this section, we aim to detect possible stay points for finding out stay regions. According to the result of shape-clustering, we used the existing method to detect stay points for each trajectory cluster. In existing

**Algorithm 1** Shape-Clustering Algorithm

**Input:** A trajectory $T_i = p_1p_2p_3...p_j...p_{len_i}$, A trajectory $T_j = p_1p_2p_3...p_j...p_{len_j}$, similarity threshold $SimThres$ , distance threshold $\delta$

**Output:** Trajectory clusters

```
$SimSeg = 0$
$TotalSeg = 0$
$TS_i \leftarrow$ timestamp of $p_1$ in $T_i$
$TS_j \leftarrow$ timestamp of $p_1$ in $T_j$
while $TS_i \leq$ timestamp of $p_{len_i}$ and $TS_j \leq$ timestamp of $p_{len_j}$ do
  $Avgpoint_i \leftarrow$ average latitude and longitude of points in time interval $[TS_i , TS_i + 25]$
  $Avgpoint_j \leftarrow$ average latitude and longitude of points in time interval $[TS_j , TS_j + 25]$
  $TotalSeg \leftarrow TotalSeg + 1$
  if distance between $Avgpoint_i$ and $Avgpoint_j \leq \delta$ then
    $SimSeg \leftarrow SimSeg + 1$
  end if
  $TS_i \leftarrow TS_i + 10$
  $TS_j \leftarrow TS_j + 10$
end while
if $SimSeg$ / $TotalSeg \geq SimThres$ then
  put $T_i$ and $T_j$ into same trajectory cluster
end if
```

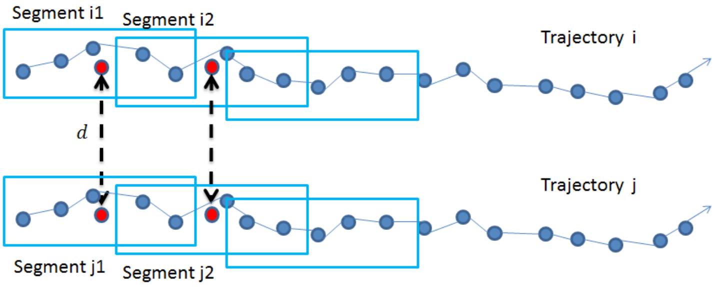


Figure 3.1: Shape-clustering

work [6] [7], stay points are detected when user stay somewhere for a while. the GPS points of trajectory must conform two criterions: 1) the distance between a GPS point and its last GPS point is very short, 2) the time difference between these two GPS point is large. In other words, if a user **does not move** or just **walk around** for a long time, the area will be determined as stay point. In this paper, we set distance threshold as 1 km and time threshold as 15 minutes in order to detect stay points. Stay point is detected when the consecutive points of a examined point do not exceed the predefined distance threshold during the specified period of time threshold.

A stay region is a summary of a set of similar stay points from different trajectories. To define the similarity between stay points and discover the stay regions, we adopt the definition of shared nearest neighbor (SNN) and SNN density-based clustering. That is, the similarity between a pair of points is measured by the number of their shared nearest neighbors.

When applying SNN density based clustering to discover stay regions, we constrain the searching range of nearest neighbors is a radius $D_h$ around the examined nodes. We define a stay point is in a stay region if each stay point of which contains at least $MinSR$ number of neighbors in the distance radius $D_h$. The points without $MinSR$ nearest neighbors are viewed as non-stay points and discarded. All the connected components in the resulting graph are clusters finally. These clusters can be considered as stay region candidates where an object often stay for certain activities. After generating the relevant stay region candidates, to avoid the region formed by traffic jam, we check whether the region is on the road exactly or not. If stay regions are located on road, the stay regions are removed from candidates since the regions may be formed by traffic jam. For example in the Figure 3.2, the result of this module are three trajectory clusters($TC_1, TC_2$ and $TC_3$) and the trajectories in the same cluster have similar shape with each other. In each cluster, there are some relevant stay region candidates($R_1, R_2, ..., R_5$) generated by stay points detection and SNN-clustering.

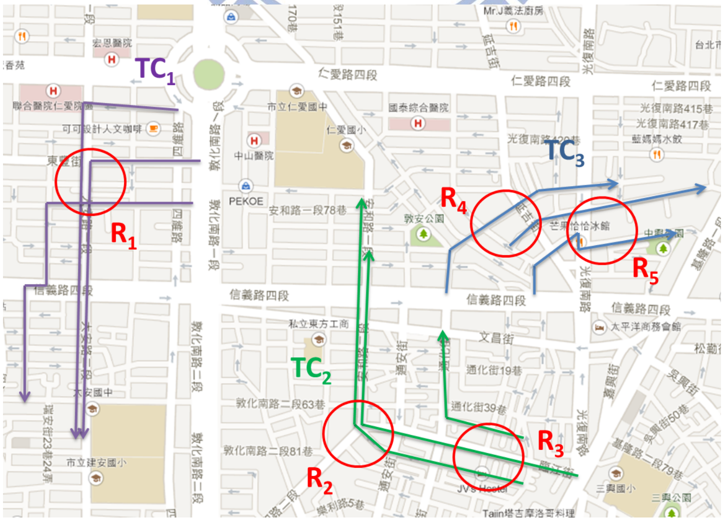


Figure 3.2: Example: Result of Region Modeling

**Algorithm 2** Algorithm of SNN-clustering

```
Input: A set of nodes, Distance threshold $Dh$, Minimum support $MinSR$
Output: A set of clusters

1 Find the MinSR-nearst neighbors in $Dh$ of all nodes.
2 Construct the shared nearest neighbor similarity graph.
3 For every node in the graph, calculate the number of links.
4 Identify core nodes which has more or equal to $MinSR$ links.
5 Identify noise nodes which is neither a core node nor linked to a core node and remove them.
6 Take connected components of nodes to form clusters.
7 Return the union of all clusters.
```

# Chapter 4

# Mobility Prediction

In this chapter, we proposed a prediction module which consists of two components: **Trajectory Cluster Selection** and **Prediction Strategy** which mainly selects the best trajectory cluster and determines the score of relevant stay region candidates respectively. Then, the relevant stay regions with top-k score will be recommended by this mobility prediction module.

## 4.1 Trajectory Cluster Selection

All of Stay regions must be in one trajectory cluster in our method. And we consider the importance of the trajectory cluster to evaluate whether a stay region will be a real stay region or not. A trajectory cluster consists of the similar-shape trajectories, and we thought it indicates some movement behaviors. Generally, movement behavior is usually relevant to time or location of a stay region. Thus, the average time and location of relevant stay region candidates in the trajectory cluster are used to determined the score of the trajectory cluster. The average time and location of relevant stay region candidates are defined as equation 4.1 and equation 4.2. And as the equation 4.3, the average time and average location of stay regions in a cluster are closer to current starting time and location, the value is closer to zero and the trajectory cluster is better. Because the movement behavior of the trajectory cluster is matched current behavior of users.

$$TC_i.time = \frac{\sum_{j=1}^{n} SR_j.time}{n}, \forall SR_j inTraj \in TC_i \tag{4.1}$$

$$TC_i.loc = \frac{\sum_{j=1}^{n} SR_j.loc}{n}, \forall SR_j inTraj \in TC_i \tag{4.2}$$

$$score_{TC_i} = \frac{\frac{|TC_i.time - query.time|}{MAX(|TC.time - query.time|)} + \frac{Distance(TC_i.loc - query.loc)}{MAX(Distance(TC.loc - query.loc))}}{2} \tag{4.3}$$

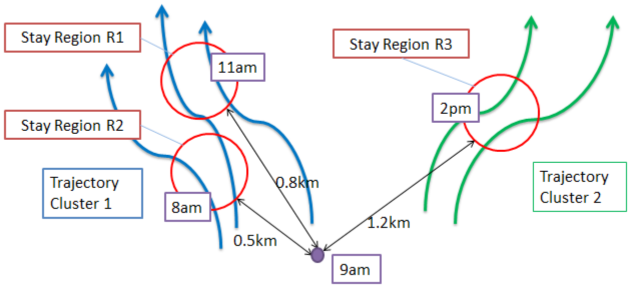


Figure 4.1: Predicting trajectory cluster by start location and time

## 4.2 Prediction Strategy

In spite of trajectory cluster selection can determine whether the relevant stay regions in which trajectory cluster are good or not, the relevant stay regions in the same trajectory cluster still should be scored. We evaluate each relevant stay region candidate by score of trajectory cluster and score of stay region itself. In addition, the score of trajectory cluster have priority over score of stay region. Thus, after defining the score of trajectory cluster, we define score functions to evaluate the probability of staying over the stay regions. We develop three Strategies: 1) $Near\ Time\ First$, 2) $Near\ Location\ First$ and 3) $High\ Frequency\ First$. $Near\ Time\ First$(equation 4.4) means that if the historical stay time on the stay region is closer to current time, the score is higher. Because we thought the closing stay region has higher probability the users will stay.

$$score_{NT,i} = \frac{1}{log_2(\Delta Time + 2)} \tag{4.4}$$

In the same manner, $Near\ Location\ First$(equation 4.5) denotes that the distance between stay region and current location, the score is higher.

$$score_{NL,i} = \frac{1}{log_2(\Delta Distance + 2)} \tag{4.5}$$

The last one is $High\ Frequency\ First$(equation 4.6), the more times the user has been stay region, the score is also higher.

$$score_{Freq,i} = \frac{Frequency_i}{Frequency_{max}} \tag{4.6}$$

Moreover, we consider that different users may have good effect by using different score functions, so the **Weighted Average** of these three score functions will be adopted. As the equation 4.7, the combination of score functions can be set different $\alpha$,$\beta$ and $\gamma$ for different user. In general, the next stay location often near the current location and the time at next stay location often near the current time, so $\alpha$ and $\beta$ can be set larger than $\gamma$. Otherwise, if the user often stay some specific location many times so that we can use *High Frequency First* to predict the next stay region very well, then the $\gamma$ can be set larger. After this section, we evaluate the effect of these three criterions and the combination of score functions in experiment section.

$$score_{Comb,i} = \frac{\alpha \times score_{NT,i} + \beta \times score_{NL,i} + \gamma \times score_{Freq,i}}{\alpha + \beta + \gamma} \tag{4.7}$$

# Chapter 5

# Experimental Results

In this chapter, we give a brief introduction of our experimental environment including the testing datasets and the metric we used to evaluate the accuracy. The experiment result with other comparison target and impact of parameters also emerge in following section.

## 5.1 Environment

### 5.1.1 Dataset Description

We use a real-world datasets: GPS data of trips from a website called @trip (http://www.a-trip.com/). @trip is a platform let users can upload their travel logs or check-in data and share these data for other users. We extract a part of data which consists of 1,243 users, 14,039 trajectories and 13,192,283 GPS points. In the following experiment, due to how regular the user visited some places will affect the entropy of their stay regions, so we defined three user types and collected the users with the same user type which is according to the entropy of their stay regions. In other words, the users with the entropy less than 0.3 are user type 1, the users with the entropy equal or more than 0.3 and less 0.7 are user type 2, the others are the user type 3 since the range of entropy is from 0 to 1. We use the trajectories of these users during 4 months for query and groundtruth has been labeled also in the time duration.

### 5.1.2 Evaluation Metric

As in many research articles, to evaluate the prediction accuracy, we use the precision to evaluate the effect of our prediction. For each user, we use labeled stay region from historical trajectories as groundtruth. For each query, our system will recommend $k$ relevant stay regions and if one of these $k$ relevant stay regions is in the list of groundtruth, we consider it as a hit. Then, we define the precision as number of hits over $k$.

In other hand, groundtruth can be ranked actually because if we aim to find out the next stay region, the nearest stay location has more probability become the next stay region. So, groundtruth can be ranked by time and location if the time or location of relevant stay region closer current time or location, the stay region will be in the front of ranking. Then, we use nDCG to evaluate the effect of our ranking of relevant stay regions.

The other evaluation metric is average distance error. We use it to identify the next stay region which we predicted whether has high accuracy or not. If the result of prediction is near by the groundtruth of next stay location, the average distance error will be low.

Table 5.1: The Statistics of Sample of Users

| User id | Entropy(Stay Region) | #Traj | #TC | #SP | #SPC | #SPC(Shape-Clustering) |
|---|---|---|---|---|---|---|
| 603 | 0.283 | 486 | 22 | 100 | 16 | 21 |
| 3898 | 0.591 | 1727 | 98 | 681 | 80 | 85 |
| 501 | 0.825 | 150 | 11 | 92 | 13 | 15 |

Table 5.2: The Description of Parameters.

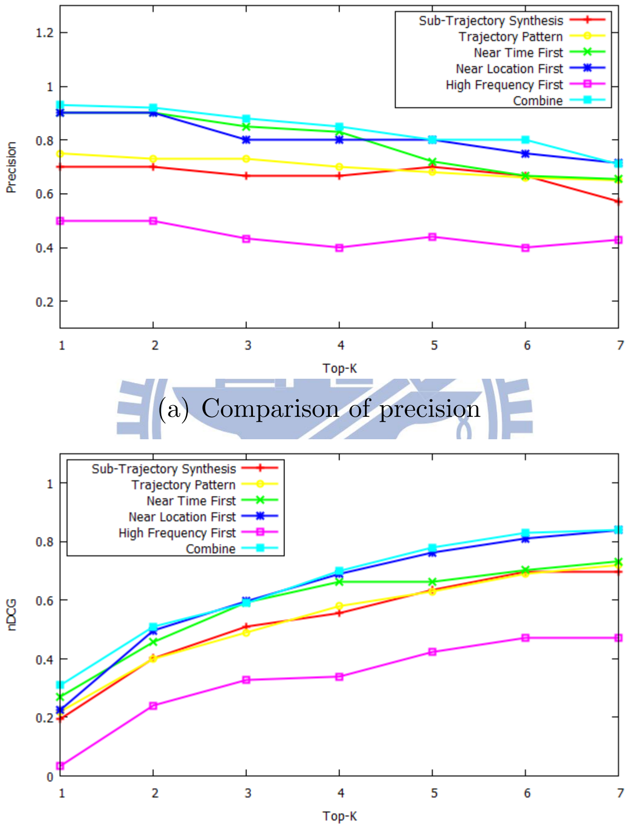
| Parameter | The description of parameter |
|---|---|
| $\delta$ | distance threshold in shape-clustering(km) |
| $\tau$ | period of a segment in shape-clustering(second) |
| $\upsilon$ | speed threshold in stay point detection(km/hr) |
| $t$ | time threshold in stay point detection(minute) |
| $\epsilon$ | entropy threshold in stay point detection |
| $Dh$ | distance threshold in SNN-clustering(km) |
| $MinSR$ | minimum support in SNN-clustering |

## 5.2 Performance Evaluation

In this section, we evaluate the accuracy and observe the impact of some parameters in our methods. In addition, we shows some experiment results for comparison between method in this paper and some of existing works.

### 5.2.1 Evaluation of Next Location Prediction

In [2], to predict destination, compute the posterior probability for any given query sub-trajectory. In [3], they construct the decision tree called Trajectory Pattern Tree to predict the next stay location. To compare with it, we use average distance error and precision to evaluate. In this part of experiment, we predict all the possible stay regions and next stay region. In figure 5.1(a) and 5.1(b), although using **High Frequency First** can not get better effect, The **Near Location First** and **Combine** methods have better precision and nDCG value than comparison target.

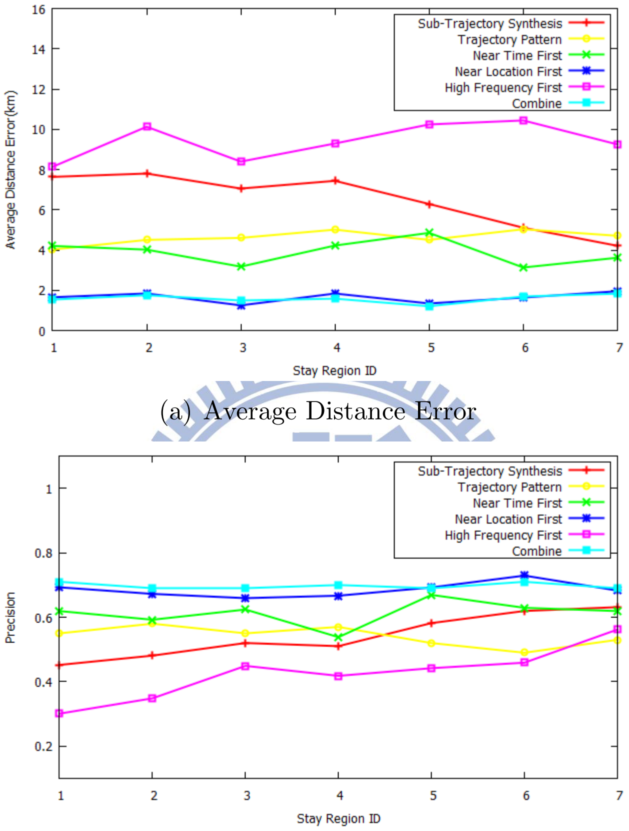


(a) Comparison of precision

(b) Comparison of nDCG

Figure 5.1: Comparing with other prediction methods

In figure 5.2(a), We evaluate the prediction of next location by average distance error. In this figure, x-axis denotes the region id which indicates the real stay location in groundtruth sequentially. For example, region id 3 is the next stay region when user is at region id 2. In figure 5.2(a) shows that both the **Combine** method and **Near Location First** have less distance error than sub-trajectory synthesis methods in [2] and prediction by using trajectory pattern in [3].



(a) Average Distance Error

(b) Precision

Figure 5.2: Average distance error and precision for next stay region prediction

We also evaluate the prediction of next location by precision. In figure 5.2(b), we can figure out the comparison target [2] has higher precision when the number of predicting region id getting large. Because it used the sub-trajectory for query, the accuracy will be higher when the length of sub-trajectory for query is longer. However, in figure 5.2(b), the scoring method **Near Location First** and the **Combine** have higher precision than it.

### 5.2.2 Accuracy

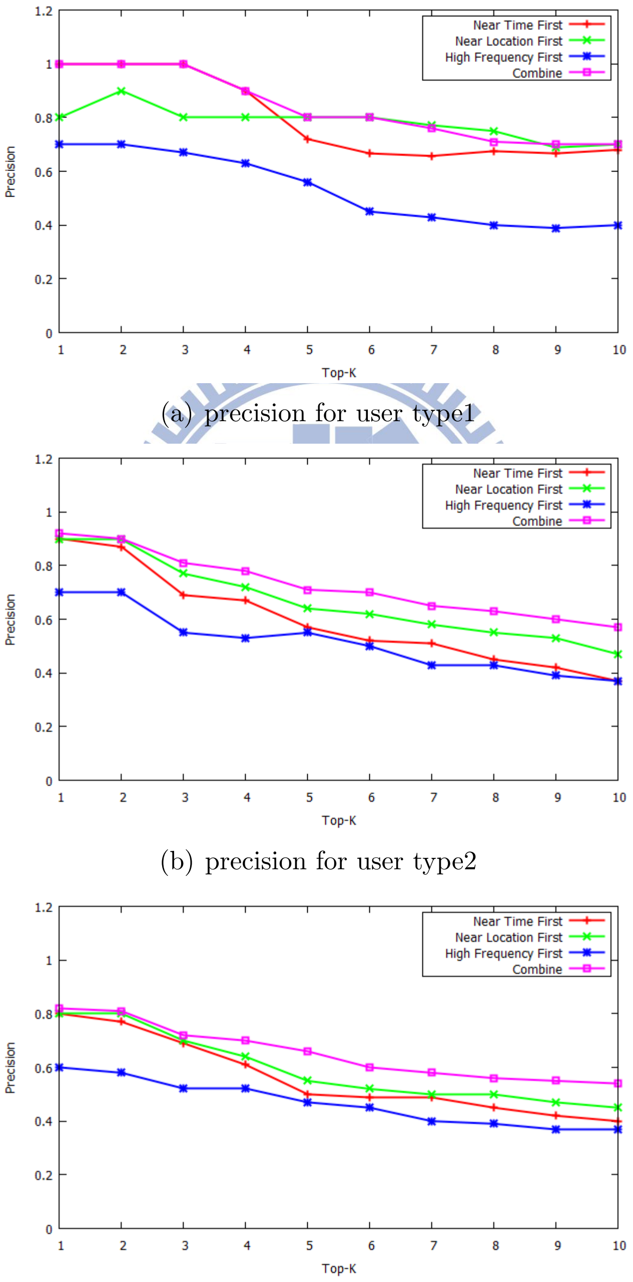
In the following, we describe our result and compare the effect of different score function. The figure 5.3(a)(data from user type 1) shows both the **Near Time First** and **Near Location First** these two score function can get higher precision than **High Frequency First**, even the $k$ increase to 10, the precision can reach to 70%. Due to **High Frequency First** consider the frequency, but user has been some stay regions several times can not imply these stay region will be next stay location. Moreover, the combination of three score functions shows by purple line has higher precision than other score functions. And figure 5.3(b)(data from user type 2) and figure 5.3(c)(data from user type 3) also show the **Combine** can get higher precision. But, in these two figures, average precision is lower than figure 5.3(a) because the regularity of visited stay regions is less.

The figure 5.4(a), figure 5.4(b) and figure 5.4(c) are the experiment result of comparing of three score function and combination of three score functions by nDCG. The **Combine** gets higher nDCG value in these figures.

## 5.3 Impact of parameters

### 5.3.1 Impact of Shape-clustering

The **shape-clustering** play a important role in our framework. So, we compare the using shape-clustering and without using shape-clustering by precision and nDCG. In the figure 5.5 and figure 5.6, the thick line denotes using shape-clustering and thin line denotes without using shape-clustering,

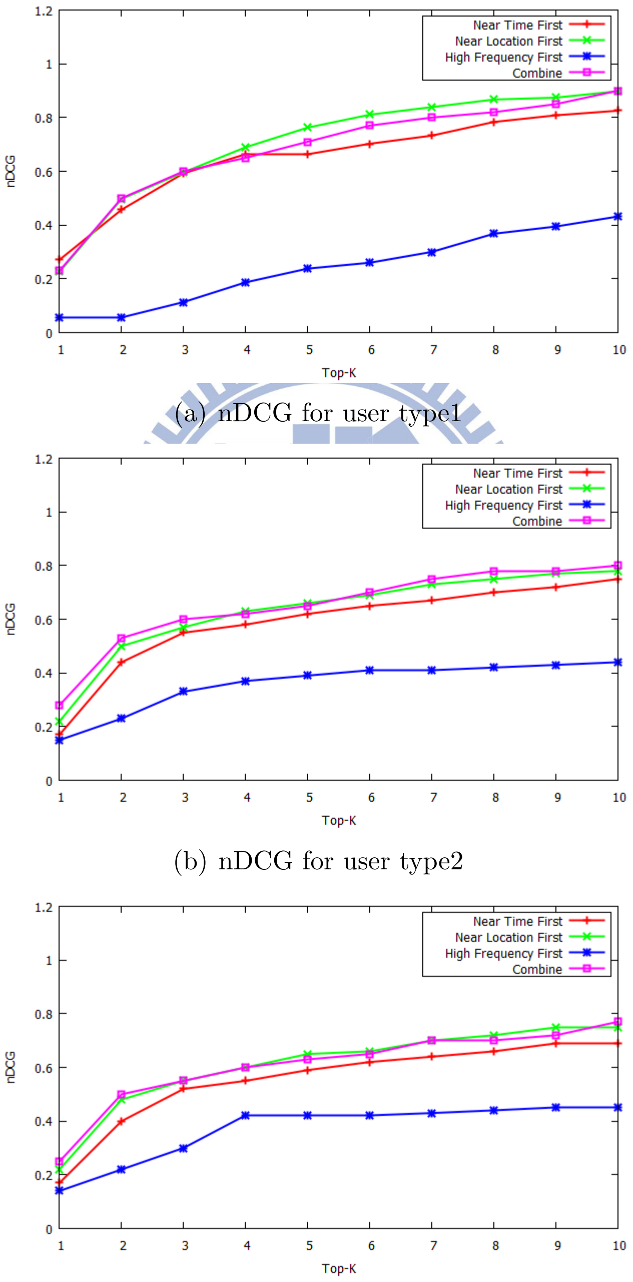


(a) precision for user type1

(b) precision for user type2

(c) precision for user type3

Figure 5.3: Precision for different user types



(a) nDCG for user type1

(b) nDCG for user type2

(c) nDCG for user type3

Figure 5.4: nDCG for different user types

then we can observe the precision and nDCG value are better by using shape-clustering obviously.

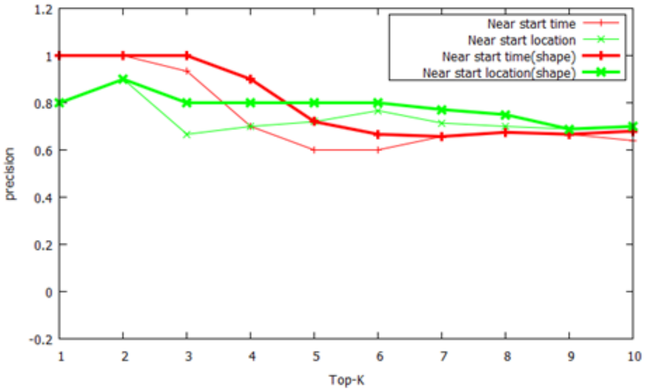


Figure 5.5: Precision (with shape-clustering)

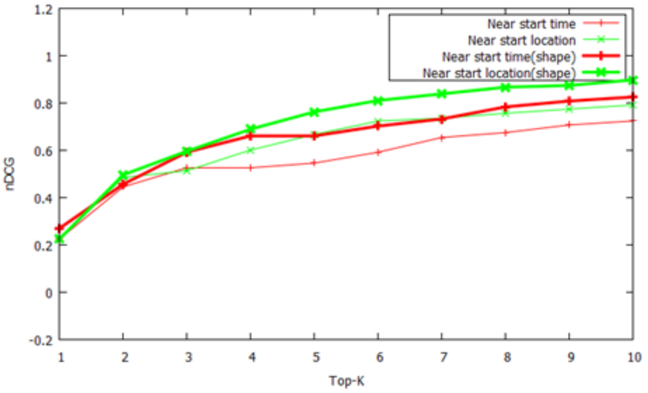


Figure 5.6: nDCG (with shape-clustering)

### 5.3.2 Impact of Parameters in Shape-clustering

In the table 5.2, $\delta$ is a parameter in shape-clustering, which indicates distance threshold, if distance between two trajectories segments less than $\delta$, the two segments are determined as similar segments. More similar segments implies the two trajectories are more similar and more similar trajectories implies the trajectory clusters will decrease. In figure 5.7 shows that when $\delta$ increase, the number of trajectory clusters is small. In other hand, figure 5.8 also shows that when $\delta$ increase, the number of relevant stay regions is small.

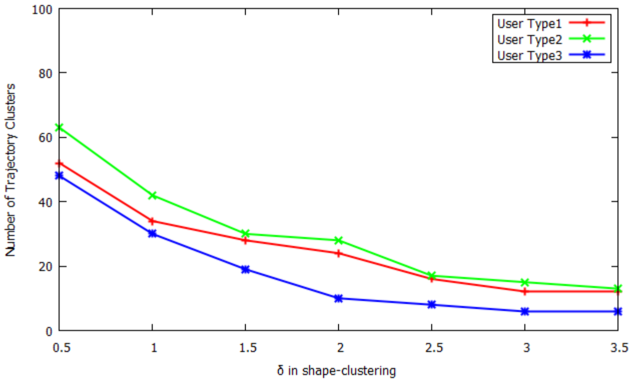


Figure 5.7: Impact of parameter $\delta$ (Number of trajectory clusters)

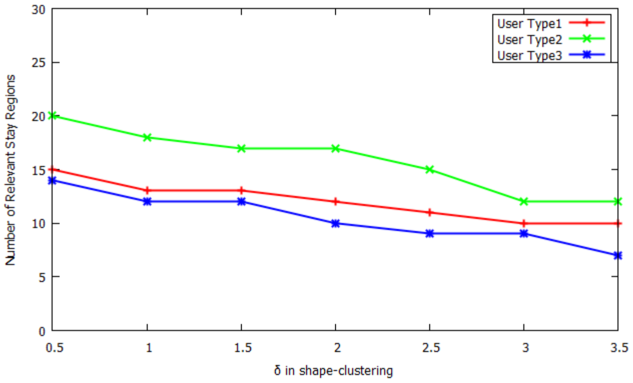


Figure 5.8: Impact of parameter $\delta$ (Number of relevant stay regions)

However, $\delta$ should be moderate, because the too large or too small number of trajectory clusters and too large or too small number of stay regions can cause the low quality of prediction. In the figure 5.9 and figure 5.10, both the precision and nDCG have good effect when $\delta$ is 2.

For another parameter $\tau$ in Shape-clustering, in figure 5.12(a), figure 5.12(b) and figure 5.12(c), the number of trajectory clusters, number of relevant stay

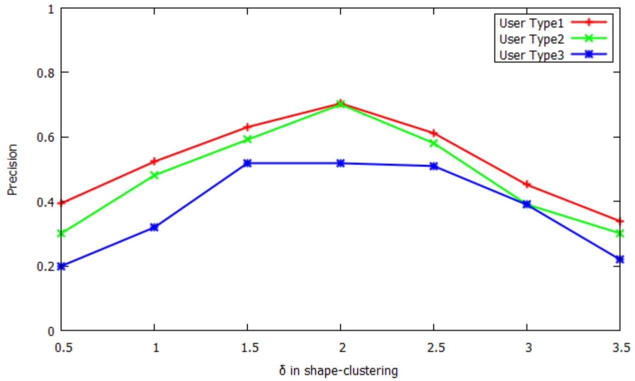


Figure 5.9: Impact of parameter $\delta$ (Precision)

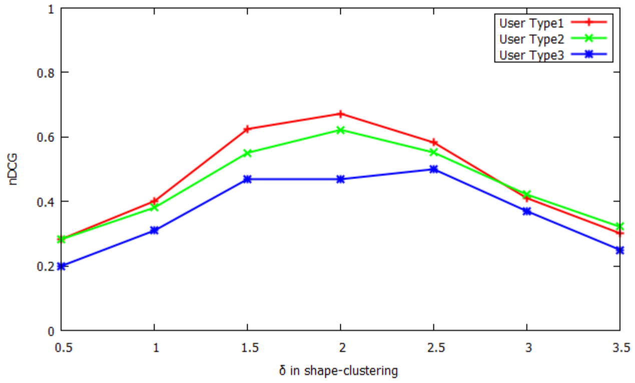


Figure 5.10: Impact of parameter $\delta$ (nDCG)

regions and precision are almost not change while the period $\tau$ of trajectory segment in shape-clustering changed because we set a overlap between a segment and the next segment. The overlap has a function of smoothing which can reduce the noise made by positioning.

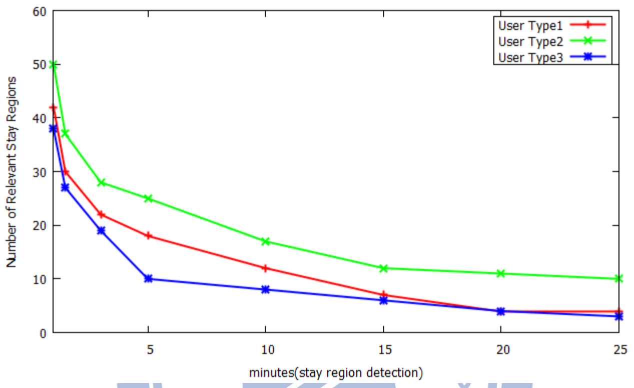
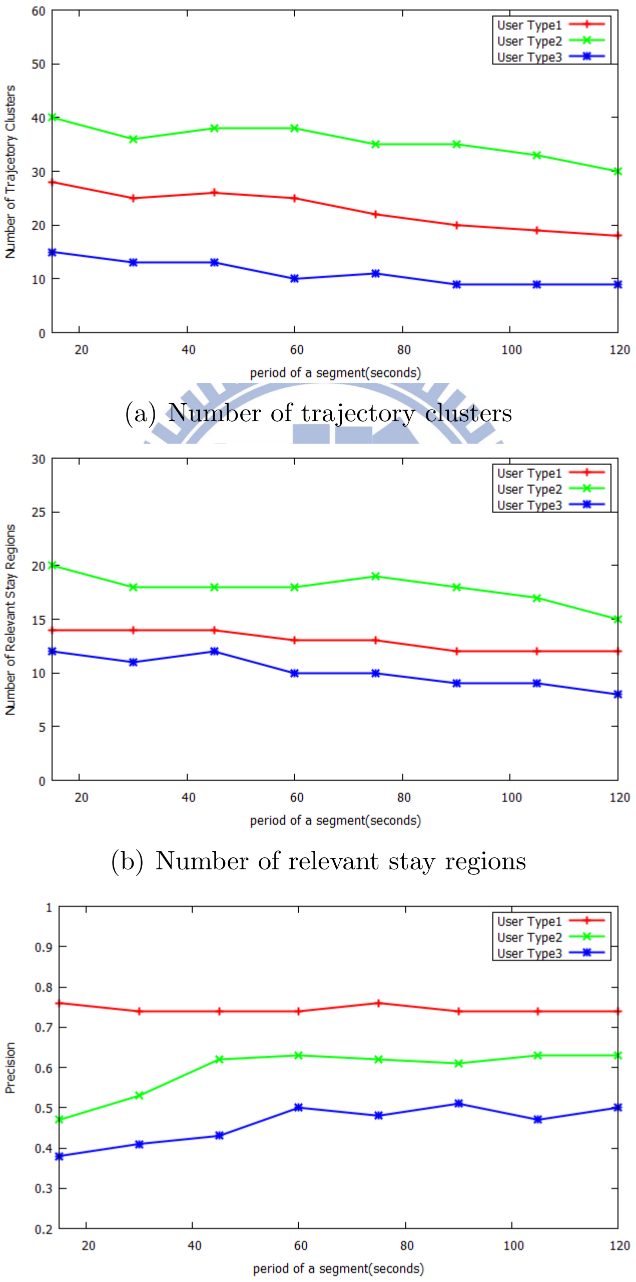


Figure 5.11: Impact of parameter $t$ (Number of relevant stay regions)

### 5.3.3 Impact of Parameters in Stay Region Detection

In the table 5.2, $t$ is a parameter in stay region detection, which indicates time threshold. A location is identified as a stay region when stay time longer than $t$. If $t$ is large, a location will be identified as a stay region more difficult. In figure 5.11, the number of relevant stay regions decrease with $t$ increasing.



(a) Number of trajectory clusters

(b) Number of relevant stay regions

(c) Precision

Figure 5.12: Impact of the period $\tau$ in shape-clustering

# Chapter 6

# Related Work

To the best of our knowledge, this paper is the first work discussing stay region prediction problem. Since we evaluated the accuracy by predicting stay regions in the experiments section, we will introduce the prediction method we adopted. In this section, We first discuss some research works which have been done in the area of destination prediction. Then, we introduce the location prediction methods and the research works related to mining stay regions.

## 6.1 Destination prediction

In existing work, Bayesian method is used to predict destination for specific individuals based on their historical transport mode [8] [9]. And Bayesian inference is the most popular framework used for deriving the probability of destinations based on historical trajectories [10] [8] [9] [11].

In other hand, Markov model has been widely applied in predicting destinations for a specific individual as well [12] [13] [14] [15]. In [2], the author uses a Markov model to offline prepare the probabilities needed to efficiently compute the posterior probability for any given query trajectory online.

Some existing work use the external information to predict destination, these external information such as the distributions of different districts (ground cover), of traveling time, of trajectories length [10] [16], the accident reports, road condition, and driving habits [11] often enhance the prediction accuracy. Even context information such as time-of-day, day-of-week, and velocity has been incorporated as the features in training the Bayesian network model for prediction [17].

## 6.2 Location prediction

Nearest-Neighbour Trajectory (NNT) method that used distance measures to identify the historical trajectory which was the most similar to the current partial trajectory [18]. Chen et al. [19] used a tree structure to represent the historical movement patterns and then matched the current partial trajectory by stepping down the tree. Trajectory pattern [4] and decision tree [3] are also used on location prediction.

## 6.3 The research related to stay location

To discover the stay regions, stay points should be detected first. The authors in [6] proposed the concept of stay point detection to discover the stay regions.

Unlike density based clustering, stay point is detected when the consecutive points of a examined point do not exceed the predefined distance threshold during the specified period of time threshold.

In other hand, Stay region is usually formed by several stay points. SNN-clustering [20] [21] is adopted by most of existing work. The concept in SNN-clustering is merge the items which have shared-neighbors. By using SNN-clustering, location with high density can be mined.

# Chapter 7

# Conclusion

In this paper, we propose the concept of relevant stay region that indicates regions along with historical trajectories and it is related to user's movement behaviors. The first component is region modelling module which aims to find out the relevant stay region candidates. We adopt a clustering method called shape-clustering which aims to group the similar-shape trajectories. Because the stay points in each non-similar-shape trajectories have different meaning. Then, detect stay points by using existing method. After detecting step, we adopt a Share Nearest Neighbor clustering(SNN) to cluster the stay points into stay regions. In the second component, we design a score function for trajectory clusters and three score function which rank the stay regions, Near Time First, Near Location First, High Frequency First. Finally, to show the preciseness and effectiveness of our framework, we present comprehensive experimental results over real datasets. The results demonstrate that our framework is able to accurately extract stay regions.

# Bibliography

[1] 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.* ACM, 2010, pp. 99–108.

[2] A. Y. Xue, R. Zhang, Y. Zheng, X. Xie, J. Huang, and Z. Xu, "Destination prediction by sub-trajectory synthesis and privacy protection against such prediction," in *29th IEEE International Conference on Data Engineering (ICDE 2013), Brisbane, Australia*, 2013.

[3] 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.* ACM, 2009, pp. 637–646.

[4] H. Jeung, Q. Liu, H. T. Shen, and X. Zhou, "A hybrid prediction model for moving objects," in *Data Engineering, 2008. ICDE 2008. IEEE 24th International Conference on.* IEEE, 2008, pp. 70–79.

[5] Y. Chen, M. A. Nascimento, B. C. Ooi, and A. K. Tung, "Spade: On shape-based pattern detection in streaming time series," in *Data En-*

*gineering, 2007. ICDE 2007. IEEE 23rd International Conference on.* IEEE, 2007, pp. 786–795.

[6] V. W. Zheng, Y. Zheng, X. Xie, and Q. Yang, "Collaborative location and activity recommendations with gps history data," in *Proceedings of the 19th international conference on World wide web.* ACM, 2010, pp. 1029–1038.

[7] C.-T. Lu, P.-R. Lei, W.-C. Peng, and J. Su, "A framework of mining semantic regions from trajectories," in *Database Systems for Advanced Applications.* Springer, 2011, pp. 193–207.

[8] N. Marmasse and C. Schmandt, "A user-centered location model," *Personal and Ubiquitous Computing*, vol. 6, no. 5-6, pp. 318–321, 2002.

[9] D. J. Patterson, L. Liao, D. Fox, and H. Kautz, "Inferring high-level behavior from low-level sensors," in *UbiComp 2003: Ubiquitous Computing.* Springer, 2003, pp. 73–89.

[10] J. Krumm and E. Horvitz, "Predestination: Inferring destinations from partial trajectories," in *UbiComp 2006: Ubiquitous Computing.* Springer, 2006, pp. 243–260.

[11] B. D. Ziebart, A. L. Maas, A. K. Dey, and J. A. Bagnell, "Navigate like a cabbie: Probabilistic reasoning from observed context-aware behavior," in *Proceedings of the 10th international conference on Ubiquitous computing.* ACM, 2008, pp. 322–331.

[12] J. Alvarez-Garcia, J. Ortega, L. Gonzalez-Abril, and F. Velasco, “Trip destination prediction based on past gps log using a hidden markov model,” *Expert Systems with Applications*, vol. 37, no. 12, pp. 8166–8171, 2010.

[13] D. Ashbrook and T. Starner, “Using gps to learn significant locations and predict movement across multiple users,” *Personal and Ubiquitous Computing*, vol. 7, no. 5, pp. 275–286, 2003.

[14] L. Liao, D. J. Patterson, D. Fox, and H. Kautz, “Learning and inferring transportation routines,” *Artificial Intelligence*, vol. 171, no. 5, pp. 311–331, 2007.

[15] R. Simmons, B. Browning, Y. Zhang, and V. Sadekar, “Learning to predict driver route and destination intent,” in *Intelligent Transportation Systems Conference, 2006. ITSC’06. IEEE.* IEEE, 2006, pp. 127–132.

[16] J. Krumm and E. Horvitz, “Predestination: Where do you want to go today?” *Computer*, vol. 40, no. 4, pp. 105–107, 2007.

[17] V. Gogate, R. Dechter, B. Bidyuk, C. Rindt, and J. Marca, “Modeling transportation routines using hybrid dynamic mixed networks,” *arXiv preprint arXiv:1207.1384*, 2012.

[18] D. Tiesyte and C. S. Jensen, “Similarity-based prediction of travel times for vehicles traveling on known routes,” in *Proceedings of the 16th ACM SIGSPATIAL international conference on Advances in geographic information systems.* ACM, 2008, p. 14.

[19] L. Chen, M. Lv, and G. Chen, "A system for destination and future route prediction based on trajectory mining," *Pervasive and Mobile Computing*, vol. 6, no. 6, pp. 657–676, 2010.

[20] L. Ertoz, M. Steinbach, and V. Kumar, "A new shared nearest neighbor clustering algorithm and its applications," in *Workshop on Clustering High Dimensional Data and its Applications at 2nd SIAM International Conference on Data Mining*, 2002, pp. 105–115.

[21] R. A. Jarvis and E. A. Patrick, "Clustering using a similarity measure based on shared near neighbors," *Computers, IEEE Transactions on*, vol. 100, no. 11, pp. 1025–1034, 1973.