

MULTIPLE ROUTE CHOICES BASED ON GENERAL GPS TRAJECTORIES ANALYZED VISUALLY

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Abstract: There are frequently more than one routes between areas. Drivers select one-of-a-kind routes with distinct issues. Such considerations, have always been a factor of hobby in the transportation area. Research of course desire behaviour are generally primarily based on small range experiments with a collection of volunteers. However, the test facts is pretty restrained in its spatial and temporal scale as properly as the practical reliability. In this work, we discover the possibility of reading direction preference behaviour primarily based on standard trajectory statistics-set, that is more realistic in a much wider scale. We broaden a visible analytic gadget to help customers handle the huge-scale trajectory facts, evaluate distinct direction picks, and discover the underlying motives. Particularly, the device consists of: 1. The interactive trajectory filtering which supports graphical trajectory question; 2. The spatial view which offers a top level view of all feasible routes extracted from filtered trajectories; 3. The aspect visualizations which provide the exploration and hypothesis production of different factors' impact on route choice behaviour, and the verification with an integrated path desire version. Applying to actual taxi GPS dataset, we document the system's performance and demonstrate its effectiveness with 3 cases.

1. Introduction

With the improvement of sensing technology, a diffusion of huge statistics has been produced in city area. Urban computing combines urban sensing, records control, analytics and offerings as an essential process, which throws light at the wealthy information of metropolis and improves human beings lives [1]. Transportation is one of the maximum essential urban computing packages. Many transportation systems analyze the town-wide human mobility records and different urban records (e.g. climate information etc.) to understand the journey behavior [2], [3] and improve the travel revel in [4]. In present day traffic networks, there are frequently a couple of routes whilst touring from one area to another. Knowledge how drivers make route choices, i.e., the path preference behaviour, is an exciting topic in transportation location. It no longer

handiest assists the town planners in the improvement of path utilization, but also helps drivers make wise travelling choices. But, path preference behaviour isn't always a clean trouble. Drivers pick out extraordinary routes thinking about various factors. The anticipated time cost is one example. Choosing the course with minimum time fee is what extensively experienced in each day existence. A few different elements may additionally influence route decision making just like the variety of visitors lighting, touring comfortableness, and so on. In the meantime, the impact of things might also exchange through the years. Drivers who care approximately the journeying comfortableness at weekends, might change it off with journey efficiency on workdays. Further rmore, the problem is even more complex whilst various factors have interaction with every other.

2. Proposed System

In this work, we discover the opportunity of analyzing path desire behavior based on extra fashionable GPS trajectory statistics, i.e., taxi GPS trajectories. In comparison to nicely-designed experiments, it takes less effort to accumulate preferred taxi GPS data. Taxi trajectories are sampled in real state of affairs and cowl a much wider spatial and temporal range. But, new challenges arise when it comes to path preference behavior analysis:

A. Extract

Extract applicable trajectories within the context of a couple of routes: unlike the experimental GPS trajectories which are confined in a fantastically limited spatial and temporal variety, the overall trajectory facts might be very complex to address. Extracting trajectories related to the routes is a huge assignment to address.

B. Raising the Hypothesis

Raise hypotheses on elements that drastically influence the direction desire behaviour: distinctive from

verification of predefined factors in hypothesis-orientated experiments, it's miles a vital mission to determine what factors to hit upon from popular GPS trajectories and how to indicate their effect on course picks.

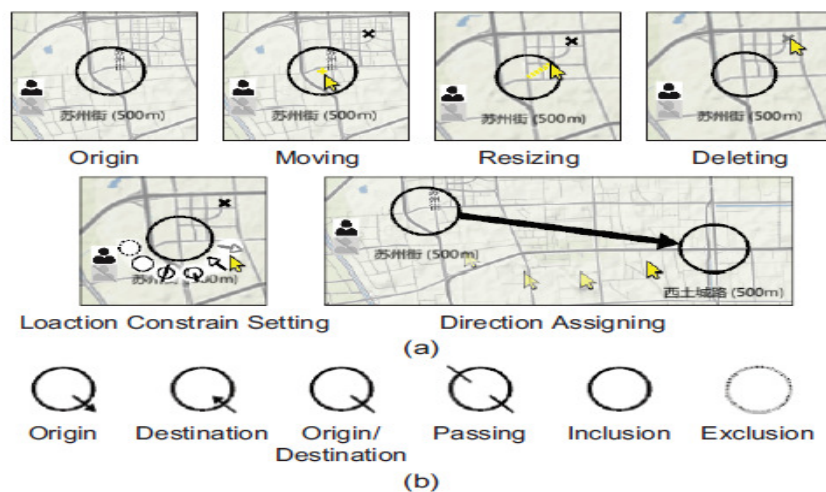
The idea is developed in following ways:

1. Trajectory Filtering
2. Spatial Visualisation of feasible routes
3. Visual Analytics

1. Trajectory Filtering

From the temporal component, a two stage temporal filter is provided: date and time. Date variety is set in the date filter out. Time variety in a day is set within the time filter, whose granularity is 10 mins. With those one-of-a-kind temporal granularities, the temporal filter permits users to query trajectories in a periodic pattern, which includes the travel journeys within the morning. From the spatial aspect, we design the filter just like Trajectory Lenses. The filter covers a round region and filters trajectories with 6 spatial constraints. The 6 constraints are defined consistent with the spatial courting between trajectory and the underlying round area: foundation, destination, beginning/vacation spot, passing, inclusive, and exceptional. The concepts are

shown in figure 1(b). For example, a filter with the starting place constraint filters trajectories beginning from the circular place. Besides the spatial constraints, there are some different geometric constraints, e.g. the center function and radius of the round region. For utilization simplicity, constraint configuration is embedded into the circular filter. As determine 1(a) shows, whilst soaring on a sure location, certain feature is waked and the corresponding handle is proven. For instance, hovering in the center of the circle invokes the moving characteristic and a + handle is visible. Clicking and dragging the + modifications the middle of the filter. Complicated queries may be constructed which combines distinctive filters in an intersection manner. Furthermore, for two or more filters, guidelines can be assigned between filters to choose trajectories following positive go with the flow guidelines. For the ease of constraint notion, constraints are explicitly encoded inside the round filter. Figure 1(b) indicates the circular filters with 6 spatial constraints respectively. On this work, the first filters are detected as the origin of Interest and vacation spot of Interest by using default.



2. Spatial Visualisation of Feasible Routes

A spatial view of all the possible trajectories can be obtained with the help of Multinomial Logit Model. One can easily fathom the model because of its lucid nature.

$$U_{ij} = \beta_i X_j + \varepsilon_i, i = 1, \dots, N, j = 1, \dots, M$$

The U_{ij} here represents utility of the i -th option assessed by the j -th person. It consists of an observable part $\beta_i X_j$ and an unknown part ε_i . The X_j vector denotes observable factors of the j -th person, like the age, weight, height etc. β_i is the coefficient vector

of option i , a major output of the model. With the maximum utility assumption, the probability of person j choosing option i can be derived as follows:

$$P_j(i) = \Pr(U_{ij} > U_{kj}), \forall k \neq i$$

To eliminate the unknown term, probability is expressed explicitly in the MNL model as:

$$P_j(i) = \frac{e^{\beta_i X_j}}{\sum_{k=1}^N e^{\beta_k X_j}}$$

From the above equation we can see that the probability varies monotonously with the observable term:

$$\beta_i \mathbf{X}_j = \sum_{i=1}^D \beta_{it} X_{jt}$$

Here, D denotes the number of observed factors, and the coefficient β_{it} depicts the impact of factor X_{jt} on option i . The model can be further simplified by setting a basic option, e.g. option m . Other probabilities are made relative to the base:

$$\ln(P_j(i)) - \ln(P_j(m)) = \ln\left(\frac{e^{\beta_i \mathbf{X}_j}}{e^{\beta_m \mathbf{X}_j}}\right) = (\beta_i - \beta_m) \mathbf{X}_j = \beta'_i \mathbf{X}_j$$

The new coefficient β'_i shows the impact of factors x_j when choosing between option i and m . This term can be expanded into $\beta'_i \mathbf{X}_j = \sum_{t=1}^D \beta'_{it} X_{jt}$. Specifically, if β'_{it} is positive, the person is more likely to option i over the base option m , when X_{jt} increases. Otherwise, the person prefers the base option m when X_{jt} increases. This exactly explains how the factor influences the final choice. The result is only meaningful when it is tested significant. So we also derive the confidence level (p -value) to verify the significance of the impact. All in all, the coefficient matrix β'_i along with the p -values, can validate the influence of factors on route choices.

In our context, it is worth studying why some people did not choose the major route. Hence, we set the most popular route (i.e. the route followed by most trajectories) as the base option m . There are 3 observable factors, i.e. departure time in a day, departure day and trajectory's length. However, not all factors X_{jt} are numerical. The trajectory's length is numerical, so it is easy to explain what happens when the trip is longer. But the other two factors, i.e. the departure time in day and departure day are ordinal. There is intrinsic chronological order but not the numeric order. For example, Saturday is chronologically later than Friday, but not numerically larger than Friday. To solve this problem, those two ordinal factors are divided into C categories. $C-1$ binary variables are introduced to indicate the absence or presence of certain category. Hence, when X_{jt} comes to the departure time in a day or departure day, it becomes a vector of dummy variables $[D_{jt1}, D_{jt2}, \dots]$:

$$D_{jtc} = \begin{cases} 1, & x_{jt} \in [r_{c-1}, r_c] \\ 0, & x_{jt} \notin [r_{c-1}, r_c] \end{cases}, c = 1, 2, \dots, C-1$$

Each binary variable acts as an independent sub-factor and its impact on route choices are studied. Different configurations of C and $[r_{c-1}, r_c]$ of each category investigate potential different impact. In our system, users are allowed to interactively divide a factor and customize dummy variables.

Table 1 shows an example of the input and output of the MNL model. Suppose the blue route is the basic route option and the departure time in a day is categorized into three categories. Then two binary

variables are imported: 7:00-9:00 and 16:00-19:00. The matrix of β'_i shows the impact of dummy variables. We can see that when departing between 7:00 to 9:00, people are more likely to choose the orange route over the blue route.

		Orange VS Blue	Red VS Blue
Departure Time in a Day	① 7:00-9:00	0.8*	-0.1
	② 16:00-19:00	-0.3	-0.1

* p -value < 0.05

3. Visual Analytics

The machine is particularly written in C++, with Qt framework. The rendering is executed with both OpenGL and Qt Graphics View framework. A 3rd-party library Graphviz is used to do the topological graph layout in course visualization. A MatLab extension is integrated within the system to carry out the MNL analysis.

Trajectory filtering supports to slender the scope of evaluation down to trajectories associated with certain origin of interest / destination of Interest pair, which might be fed into the extraction of a couple of routes and the similarly visible analysis. Numerous strategies are followed to facilitate the filtering.

In the preprocessing degree, trajectories are listed through a spatial quadtree, which divides the 2d spatial region recursively and adaptively primarily based at the distribution of trajectories' sampling points. Each quadtree node stores the IDs of trajectories that intersect it. Inside the run-time stage, a filtering operation is performed in three steps: inside the coarse filter step, the device fetches trajectories from the quadtree nodes where the circular filter locates; inside the intermediate filter step, the top N trajectories (e.g. $N =$ one hundred in this work) which fulfill the filtering constraints are lower back and rendered; inside the high-quality filter step, trajectories satisfying the filtering constraints inside the complete dataset are filtered.

To ensure interactive filtering, the first-rate filtering step isn't carried out all through dynamic filtering. For example, all through the method of transferring or resizing the round clear out, most effective the top N trajectories are returned and rendered. As soon as the clear out is settled down, the excellent filtering step is accomplished. In the meantime, when multiple filters are applied, the filtering is performed primarily based at the preceding filtered trajectories recursively, in which the query area is an awful lot smaller than the whole data set.

The overall system wouldn't require much processing power, so it can be used by most of the general public instead of targeted people with high computing power. The system's performance is tested on a Dell T3400 workstation with an Intel(R) Core(TM)2 2.66 GHz, 4 GB RAM and a NVIDIA GeForce GTX 470 GPU. The performance of filtering serves as the basis of the system so that it is crucial for the overall performance.

3. Conclusion

On this paper, we discover the opportunity of studying path desire behaviour based totally on taxi GPS trajectories. In comparison to classical direction desire analysis approach, our popular GPS based answer covers larger temporal-spatial variety as well as larger variety of samples. In this work, we list the factors that may be derived from trajectories, which defines the boundary of this standard GPS information based solution. With this, we present a visible analytic machine which helps responsibilities from course choice overview to affirm elements' impact on course choice. The machine's visualizations and interactions are designed cautiously in keeping with task-oriented concerns. The system allows interactive visual exploration in large trajectories and factors exploration with path preference version.

Within the future, we would love to apply the system to greater datasets. As an example, making use of trajectory datasets in distinct areas, we possibly are capable of evaluate the route preference behaviour of drivers over unique regions. In the meantime, we would really like to improve and enlarge our system regarding the contemporary barriers. Considering that the input factors are constant, we can improve the system to help the advent of factors. As an example, OD distribution can be one of the feasible trajectory related elements. Any other interest factor is to increase to the device with course advisory feature. By taking the evaluation of path preference, it is feasible to suggest routes by way of taking different factors into consideration and degree the fitness of course.

4. Future Work

This system can be used by well-known shipping companies like UPS, DHL, FedEx for efficient route selection which can save time and money for them. And also it can be used by general users to get to know about the better routes for a particular destination of interest.

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