Detecting Anomalous Trajectories

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CS6720: Data Mining

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What are anomalous trajectories?

An anomalous trajectory has one of the three properties:-

- Longer than usual A deliberate detour by a taxi driver.
- Shorter than usual A short-cut.
- An unusual route
 A less frequently travelled route.

Dataset

This is a sample of T-Drive GPS trajectory dataset.

- GPS traces of about 10,357 taxis from the city of Beijing.
- Total distance exceeds 9 million kilometers.
- Sampling rate once in 20 seconds(approx).
- About 15 million points.

The format of a trajectory point is

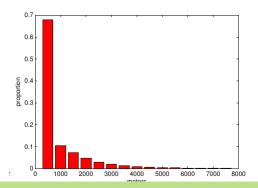
< taxild, longitude, latitude, timestamp >



Data Preprocessing

Representing Points

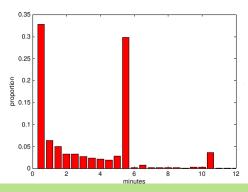
- □ We divide the city into grid cells of equal size.
- \square Each point is represented as (X,Y) coordinates.
- The average distance between consequtive points in a trajectory is approximately 633m. We chose the grid cell size as 400m $\approx \frac{623}{\sqrt{2}}m$



Data Preprocessing

Processing GPS traces to obtain trajectories

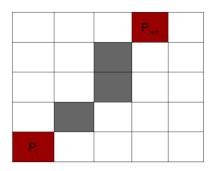
- We have collection of GPS trace points corresponding to each taxi for a week.
- We divide the collection of points into trajectories.
- We choose time threshold as 6 min. We chose this value by examining the time statistics of the data.



Data Preprocessing

Augmenting trajectories

- Trajectories now can contain non-adjacent grid points.
- $\hfill\Box$ We introduce grid points to make the trajectory continuous.
- □ As the sampling rate is high, the number of points introduced is not high.



Final Database

■ Trajectory Database

Each trajectory has a unique ID. The database entries are:-

- □ *Key*− Trajectory ID
- □ *Value* String containing the (X,Y) coordinates of points in the trajectory in order.
- Grid Database

This is an *inverted index* of Trajectory database. The entries are:-

- \square Key-String (X,Y) corresponding to the grid coordinate
- □ *Value* String containing the tuples (*trajID*, *position*) where the grid occurs in *trajID* at the specified position.

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Isolation-based

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- Doesn't use complex distance and density measures and reduces cost of computation
- Highly scalable and can handle large datasets with large number of irrelavant features

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- We construct several such trees and each time we make note of the depth of the node containing the item.

■ The anomaly score is calculated as:—

$$s(x) = 2^{-\frac{E(d(x))}{c(n)}}$$

where,

- x is the item for which we are calculating the anomaly score
- d(x) is the average depth of x over all the trees constructed.
- *n* is the number of distinct points in the initial set
- c(n) normalizes the average depth. This required because if we start with a bigger set, the tree is likely to be deeper.

$$c(n) = 2 \times H(n-1) - \frac{2(n-1)}{n}$$

where H(i) = ln(i) + 0.5772156649 (Euler's constant).

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- No commmon threshold or parameter is chosen for itemsets with different support. It is homogeneous (in some sense).

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If trajectory corresponds to a not-so-frequently-used path, then it contains grids not visited by other trajectories. It will have lesser depth.

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- Handling of loops.

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- But, the number of trajectories left in the last node should also play a role in the test trajectory's anomaly score.

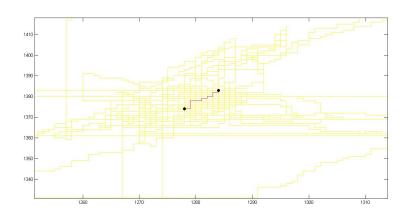
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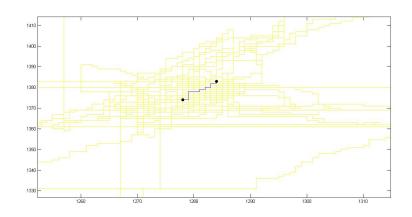
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■ If we increase *Depth* with order *N*, the number of trajectories between the *source* and *destination* would also play a role.





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- For each point p in the test trajectory, we take all the trajectories under consideration that contain this point D_p .
- We calculate the mean μ and deviation σ of the number of times a trajectory passes through point p.
- A trajectory is classified as anomalous if:

$$N_{test,p} \ge \mu + 2\sigma$$
 or $N_{test,p} \le \mu - 2\sigma$

Empirical Evaluation

- Manually labelled trajectories between few source and destination pairs.
- Evaluated our model using these trajectories as test dataset.
- Measures used:

$$\begin{aligned} \textit{Detection rate}(\textit{dr}) &= \frac{\textit{TP}}{\textit{TP} + \textit{FN}} \\ \textit{False alarm rate}(\textit{fpr}) &= \frac{\textit{FP}}{\textit{FP} + \textit{TN}} \end{aligned}$$

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dr	81%
fpr	12%

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- Weight based splitting of nodes instead of binary splitting. This will take the the distance of a point in a trajectory from the point in the test trajectory under consideration.