CZ4079 Final Year Project

A Machine Learning-Based Approach to Time-Dependent Shortest Path Queries

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Agenda

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Introduction: Problem

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- A **query** $Q(u, v, t)$ that asks for a shortest path from u to v departing at time moment t

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- **Unsupervised learning** is employed to figure out the time-dependent edge costs

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- **Unsupervised learning** is employed to figure out the time-dependent edge costs
- A modified Dijkstra's algorithm calculates a shortest path on the fly

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Introduction: Challenges

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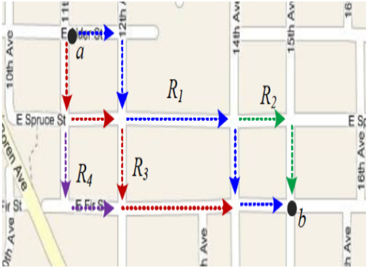

Introduction: Challenges

- Arbitrary u and v
- Sparse sample points
- Limited GPS accuracy

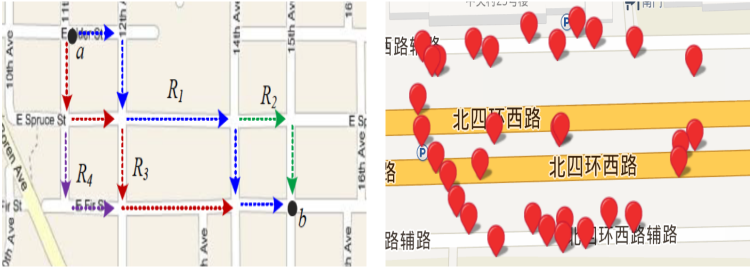

Figure 1: Examples of challenges

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Preliminary Processing: Data Description

- Is collected from Computational Sensing Lab at Tsinghua University
- Contains 83 million GPS records from 8,602 taxis in Beijing during May of 2009

Field	Explanation
CUID	ID for each taxi
UNIX_EPOCH	Unix timestamp
GPS_LONG	Longitude in WGS-84
GPS_LAT	Latitude in WGS-84
HEAD	Heading direction
SPEED	Instantaneous speed (m/s)
OCCUPIED	Hired (1) or not (0)

Table 1: A summary of the seven original fields

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Preliminary Processing: Reverse Geocoding

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Figure 2: An example of China GPS shift problem

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- China GPS shift problem: WGS84 v.s. BD09
- Solution: WGS84 $\xrightarrow{Baidu\ \ API}$ BD09 $\xrightarrow{Baidu\ \ API}$ Street

Figure 2: An example of China GPS shift problem

Preliminary Processing: Outlier Detection

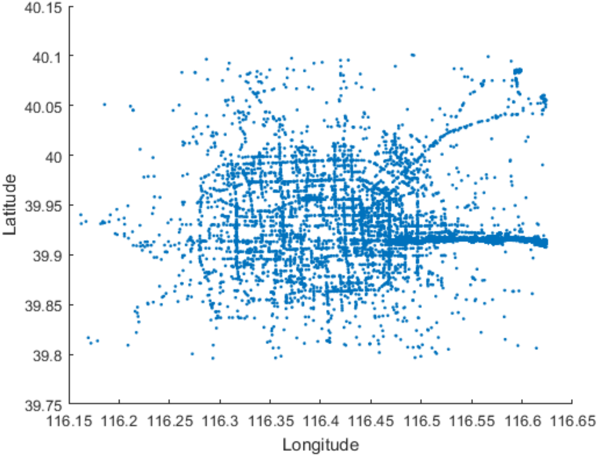

Figure 3: An example of outliers

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Preliminary Processing: Outlier Detection

Theorem (*Majority Clustering Theorem*)

If a **reasonable reverse geocoder** is used to reverse-geocode a set of GPS data points which are mapped to a particular street *in reality*, then, when plotted on a 2-D plane, majority (more than 50%) of the points must be clustered together to form a rough shape that is similar to the shape of the street that they are supposed to be mapped to.

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Two-step procedure:
Outlier Detection = Outlier Identification + Outlier Removal

Preliminary Processing: Outlier Detection

Outlier Identification: Clustering

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Outlier Identification: Clustering

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Outlier Removal: Distance Threshold d_{max}

- Assign sample points to legal centroids no farther than d_{max}
- Remove all “orphan” sample points
- Use real physical distance on the Earth
- Set $d_{max} = 30$m or 50m

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Preliminary Processing: Outlier Detection

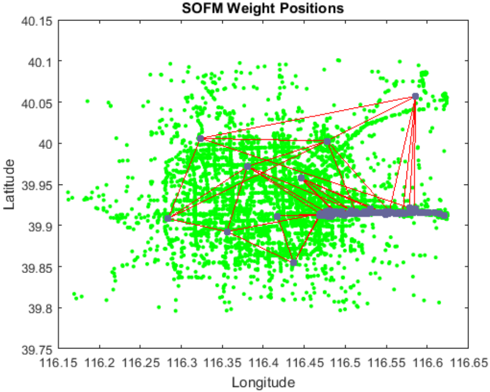

Figure 4: A plot of neuron positions after training

Preliminary Processing: Outlier Detection

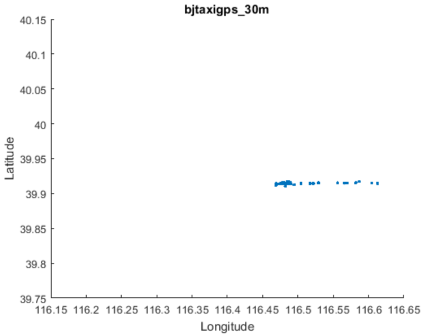

Figure 5: A plot of sample points after outlier removal

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Landmark Graph: Basic Ideas

Definition (*Landmark*)

A landmark is a road segment that is frequently traversed by taxi drivers according to the taxi GPS trajectory database.

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Step to build landmark graph

- Separate sample points into **trip**s

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Step to build landmark graph

- Separate sample points into **trip**s
- Count occurrences of each street
- Find connections between two landmarks

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Landmark Graph: Trip Identification

CUID	UTC	GPS_LONG	GPS_LAT	OCCUPIED	TRIP_ID
1	1/5/2009 0:02:00	116.39616	39.81294	0	4552265
1	1/5/2009 0:04:00	116.39575	39.82296	0	4552265
1	1/5/2009 0:07:00	116.39567	39.82774	0	4552265
1	1/5/2009 17:08:00	116.30142	39.98105	1	1
1	1/5/2009 17:10:00	116.29514	39.98419	1	1
1	1/5/2009 17:11:00	116.28959	39.98289	1	1
1	1/5/2009 17:12:00	116.28087	39.97552	1	1
1	1/5/2009 17:16:00	116.26813	39.93537	1	1
1	1/5/2009 18:11:00	116.36537	39.95019	0	4552271
1	1/5/2009 18:12:00	116.36546	39.94886	0	4552271
1	1/5/2009 18:13:00	116.35927	39.94528	0	4552271

Table 2: An example of trip identification

Landmark Graph: Frequency Counting

CUID	UTC	GPS_LONG	GPS_LAT	Street	TRIP_ID
1	1/5/2009 0:02:00	116.39616	39.81294	A	4552265
1	1/5/2009 0:04:00	116.39575	39.82296	A	4552265
1	1/5/2009 0:07:00	116.39567	39.82774	B	4552265
1	1/5/2009 17:08:00	116.30142	39.98105	C	1
1	1/5/2009 17:10:00	116.29514	39.98419	C	1
1	1/5/2009 17:11:00	116.28959	39.98289	C	1
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1	1/5/2009 18:11:00	116.36537	39.95019	B	4552271
1	1/5/2009 18:12:00	116.36546	39.94886	C	4552271
1	1/5/2009 18:13:00	116.35927	39.94528	C	4552271

Table 3: An illustration of frequency counting

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Landmark Graph: Construction

For each trip

- Select a landmark j
- Record intermediate streets while searching for the next landmark k
- Repeat the process starting from k until all streets are examined

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