Trajectory analysis

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Semantic Trajectory Mining for Location Prediction

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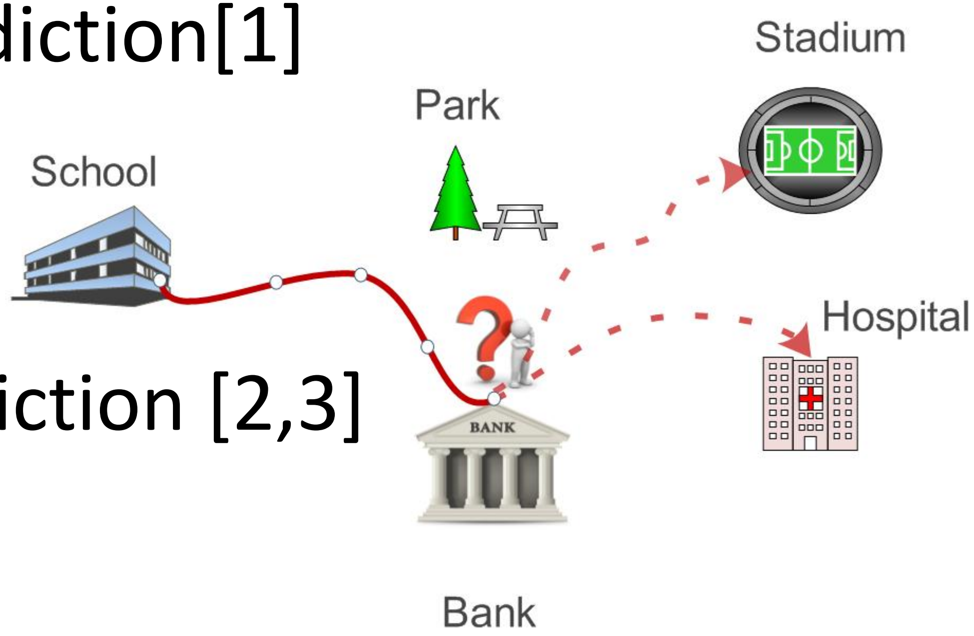
The next location prediction approaches

- Personal-based prediction[1]
- General-based prediction [2,3]



Note: further consider General-based prediction

Semantic Trajectory Mining for Location Prediction

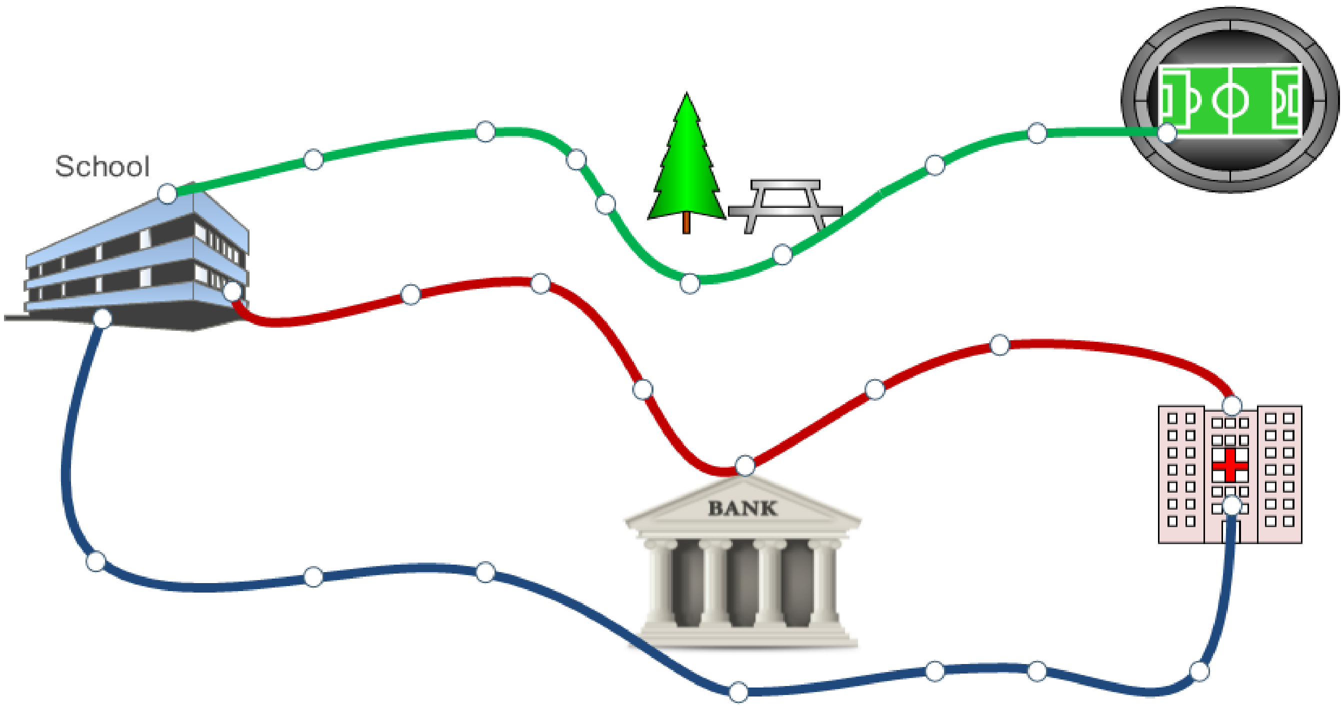
- predicting the next location of a user's movement

Input:

- GPS user's trajectories

Geographical and Semantic similarity

- Example: T_1 and T_2 – geograficaly,
  T_2 and T_3 – semantically



SemanPredict framework

- *Offline* and *Online* Modules
- Novel prediction strategy: *Semantic* and *Geographic* trajectory patterns
- MIT reality dataset [4]
  - 106 mobile users
  - Over 500,000 hours

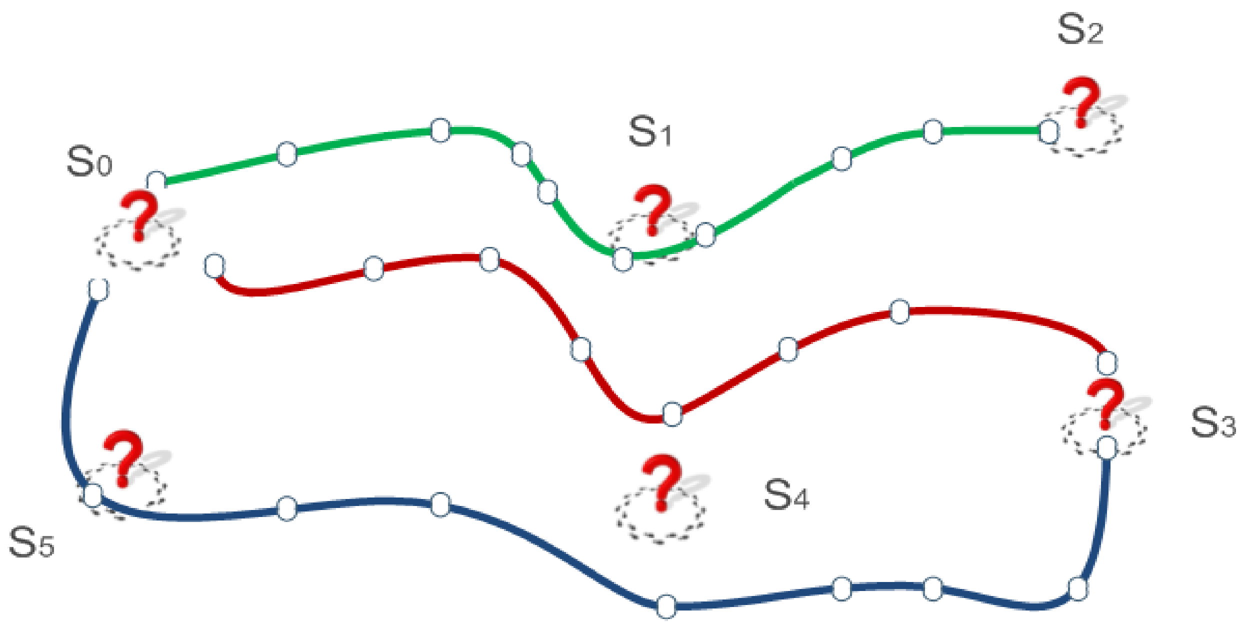
SemanPredict: offline module

1. Data preprocessing
2. Semantic mining
3. Geographic mining

SemanPredict: offline module

1. Data preprocessing:

GPS trajectories to *stay locations sequence* [1, 5]



Output: **T_1**=<S_0, S_1, S_2> ; **T_2**=<S_0, S_4, S_3>; **T_3**=<S_0, S_5, S_4, S_3>; ...

SemanPredict: offline module

2. Semantic mining:

2.1. Assign *semantic labels* to stay locations using gazetteer [6];

- Example:

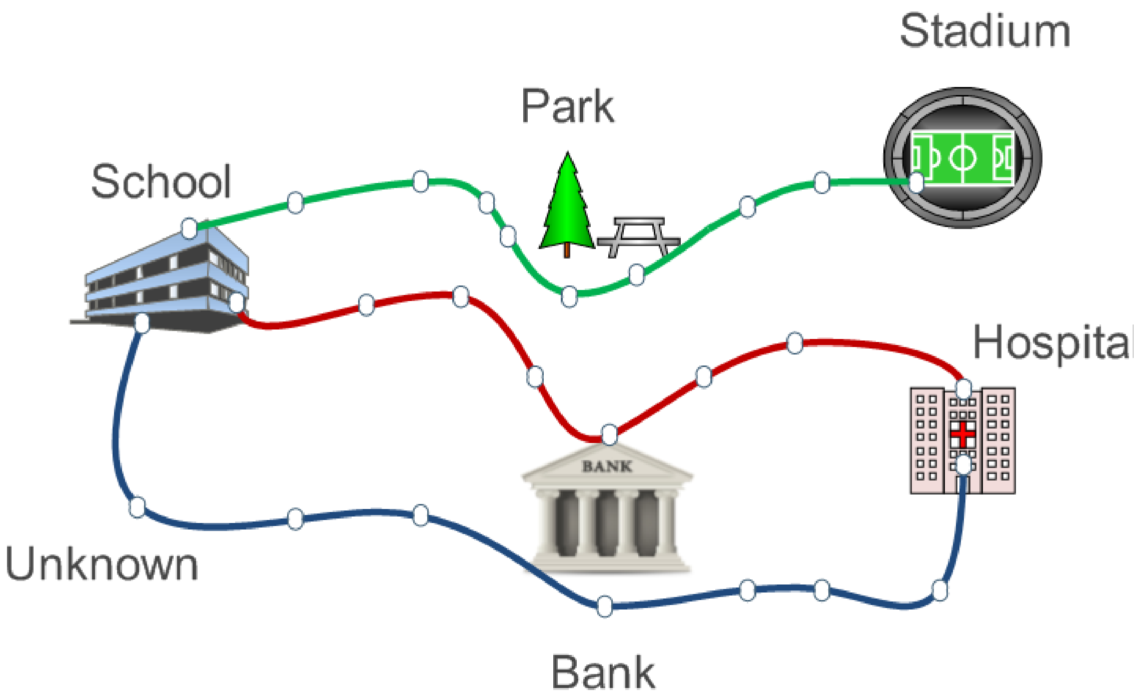
Input: $\mathbf{T_1}$=<S_0, S_1, S_2> ; $\mathbf{T_2}$=<S_0, S_4, S_3>; $\mathbf{T_3}$=<S_0, S_5, S_4, S_3>; …

Output: $\mathbf{T_1}$=<School, Park, Stadium> ; $\mathbf{T_2}$=<School, Bank, Hospital>; $\mathbf{T_3}$=<School, Unknown, Bank, Hospital>; …

SemanPredict: offline module

2. Semantic mining:

- Example: result *semantic labels*



SemanPredict: offline module

2. Semantic mining

2.2. Similar User Clustering

- Complete linkage clustering

Similarity measure: *Maximal Semantic Trajectory Pattern Similarity* [6]

SemanPredict: offline module

- Example: Longest Common Sequence(LCS)

P = <School, Park, Stadium>, Q = <School, Bank, Park, Shop>

LCS(P, Q) =<School, Park>

$$ratio(P) = \frac{1+1}{3} = \frac{2}{3} \qquad ratio(Q) = \frac{1+1}{4} = \frac{1}{2}$$

$$dist(P,Q) = \frac{1}{2} \cdot \left(\frac{2}{3} + \frac{1}{2} \right) = \frac{7}{12}$$

SemanPredict: offline module

3. Geographic mining

Input:

- stay location sequence
- clusters from **semantic mining**

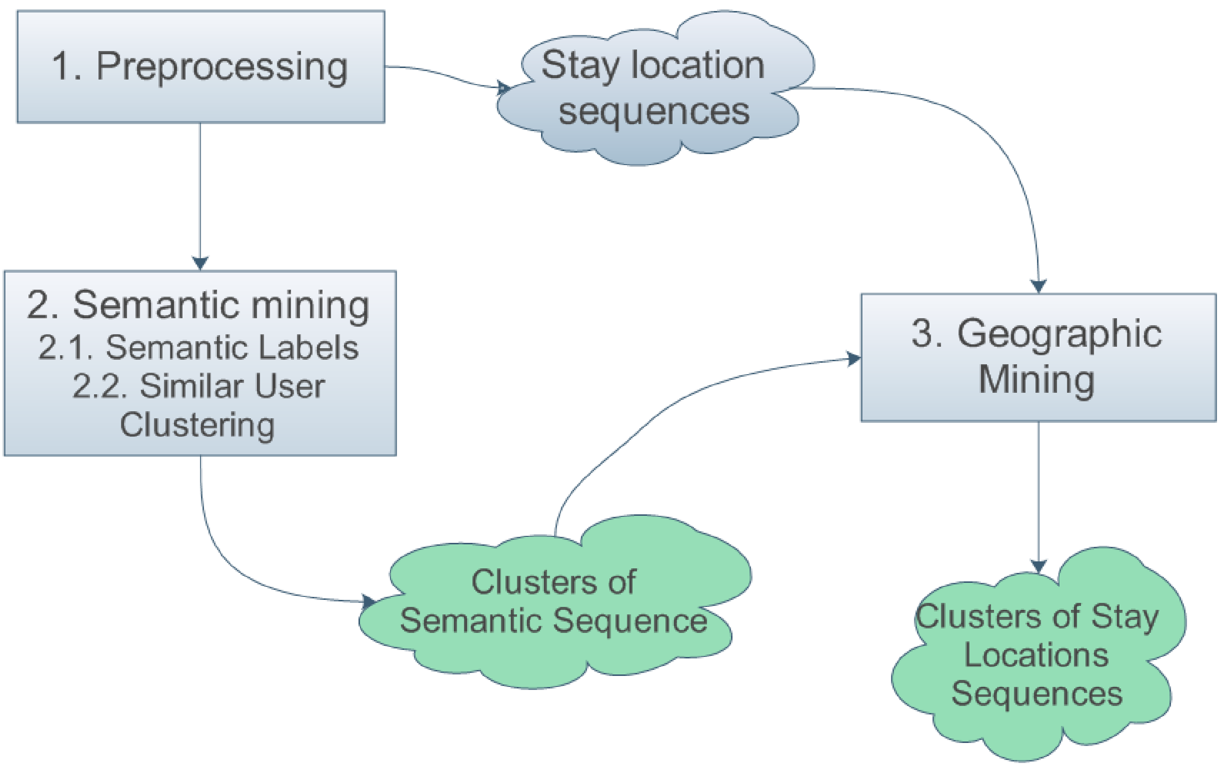
3.1. Grouping Users' Stay Location Sequences (*Prefix-Span* [9])

Output: clusters of stay location sequence based on **semantic clusters**

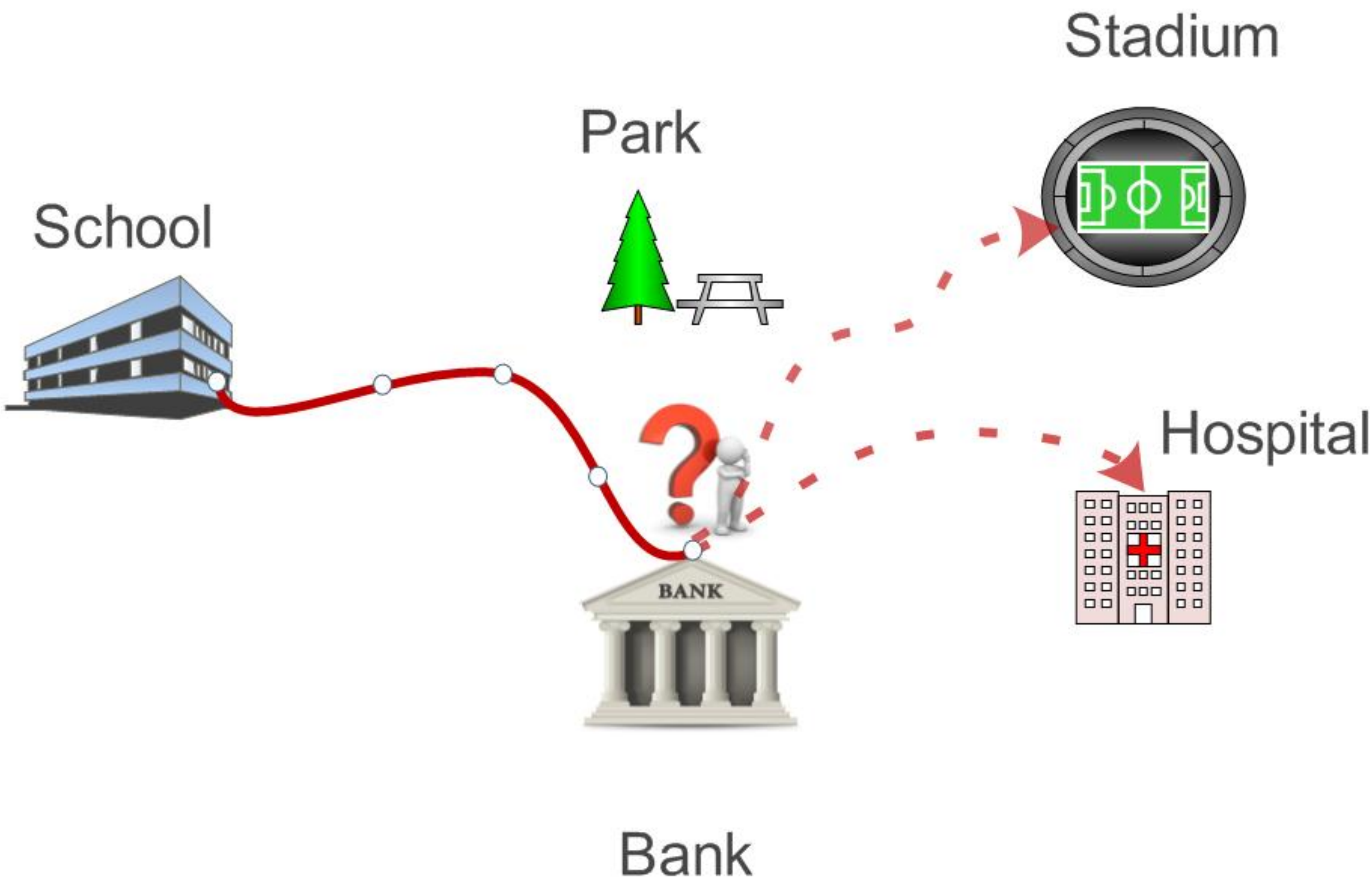
SemanPredict: offline module

- Recap

Input: GPS user's trajectories

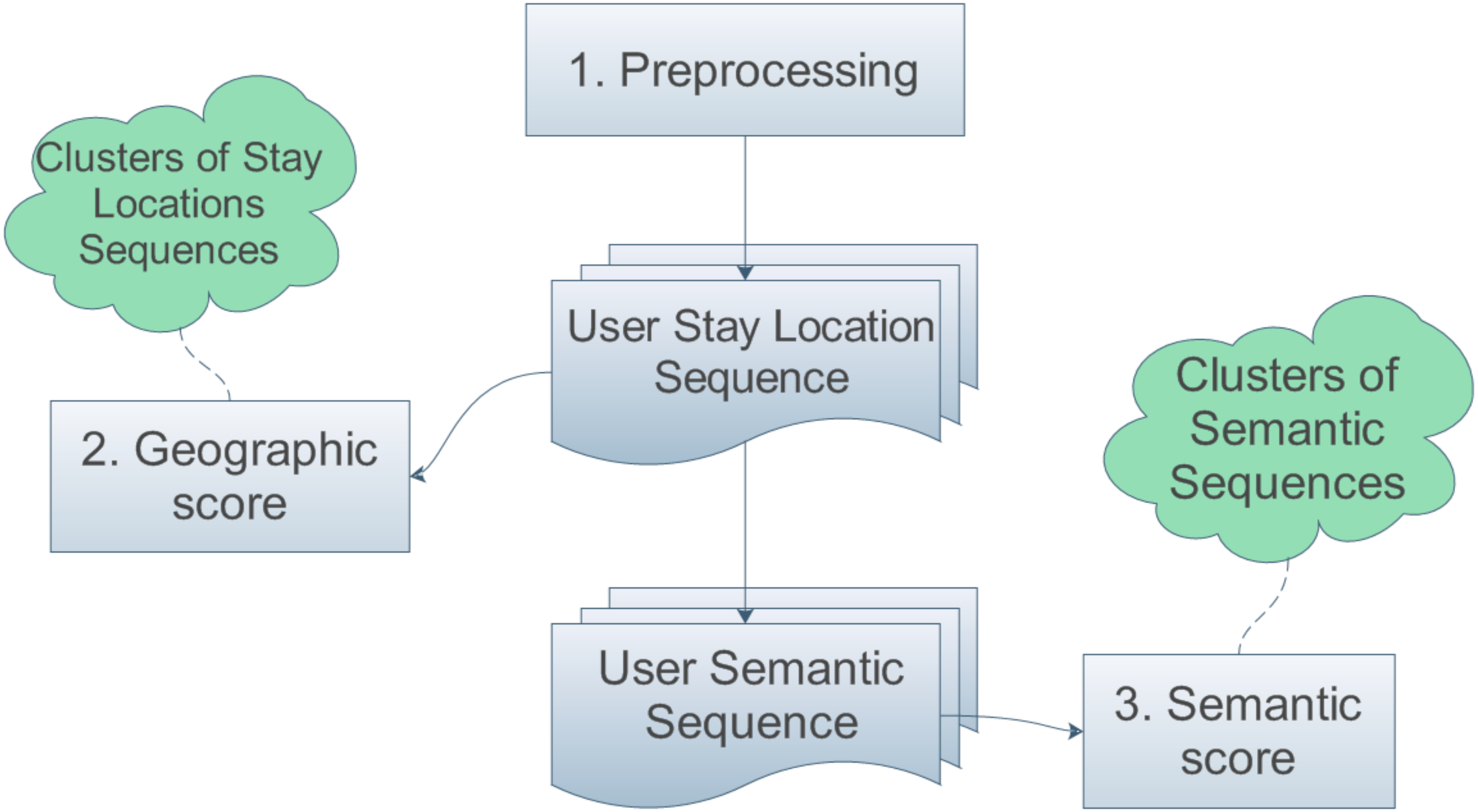


SemanPredict: online module



SemanPredict: online module

- Input: the trajectory of the user's recent moves



SemanPredict: online module

- *Matching score:*

$$Score = \beta \times GeographicScore + \left(1 - \beta\right) \times SemanticScore,$$

$$where\ 0 < \beta \leq 1$$

Note: how well the 'user behavior' matches model

Summarizing Trajectories into k-Primary Corridors: A Summary of Results

Michael R. Evans

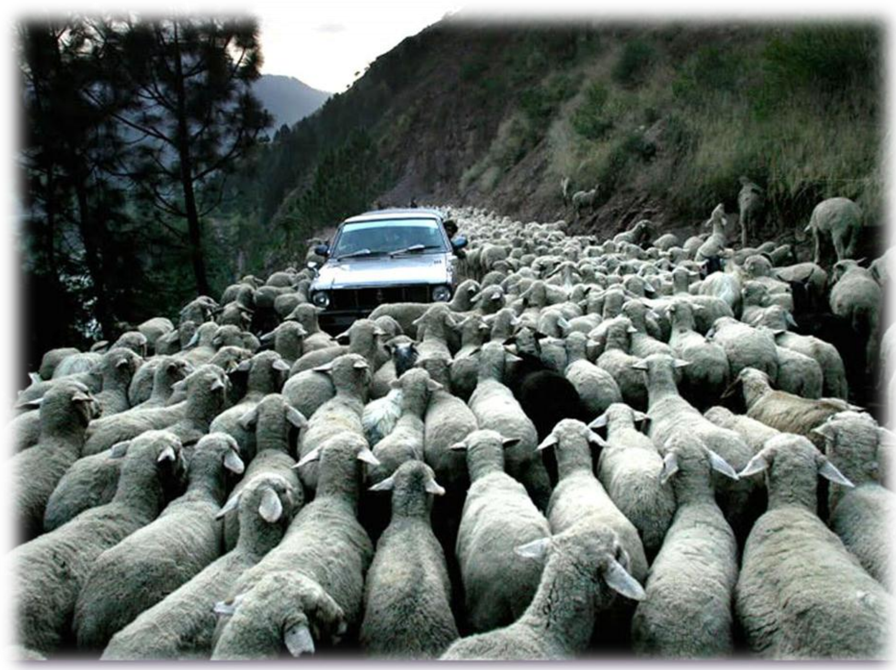
Dev Oliver

Francis Harvey

USA

Why k-Primary Corridors?

- Identifying potential avenues for access

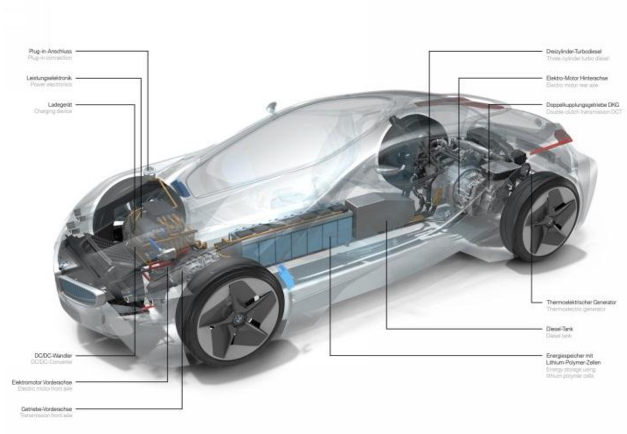


Traffic jam?!!!

- Determine **bus**, **metro** and **railway systems** corridors

Basic concepts

- **Road network**
  - Graph G = {V, E}
  - Nodes = road intersections

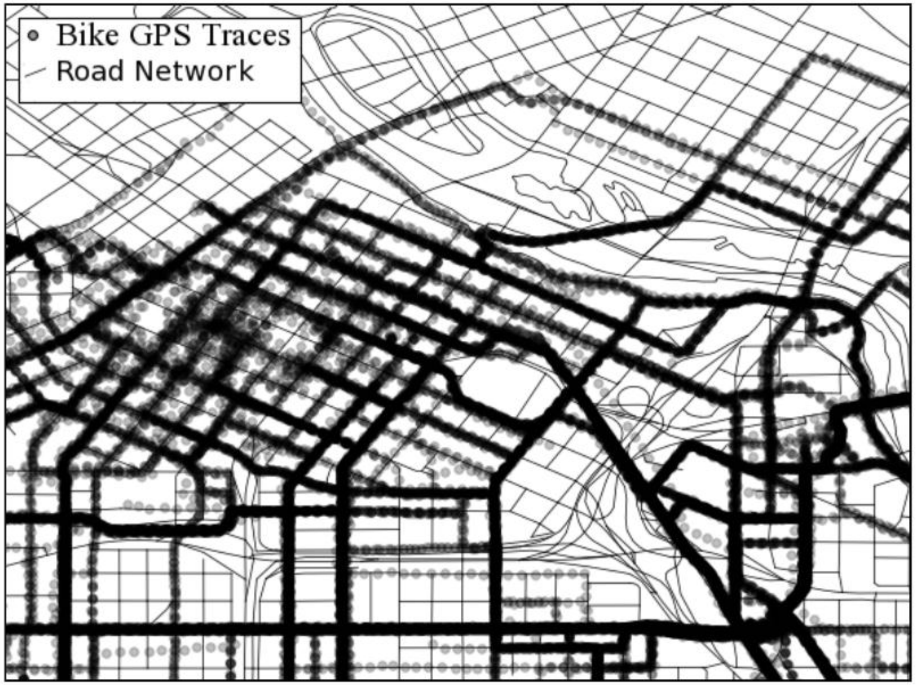


- **Track**
  - GPS trace to series of nodes and edges of road network

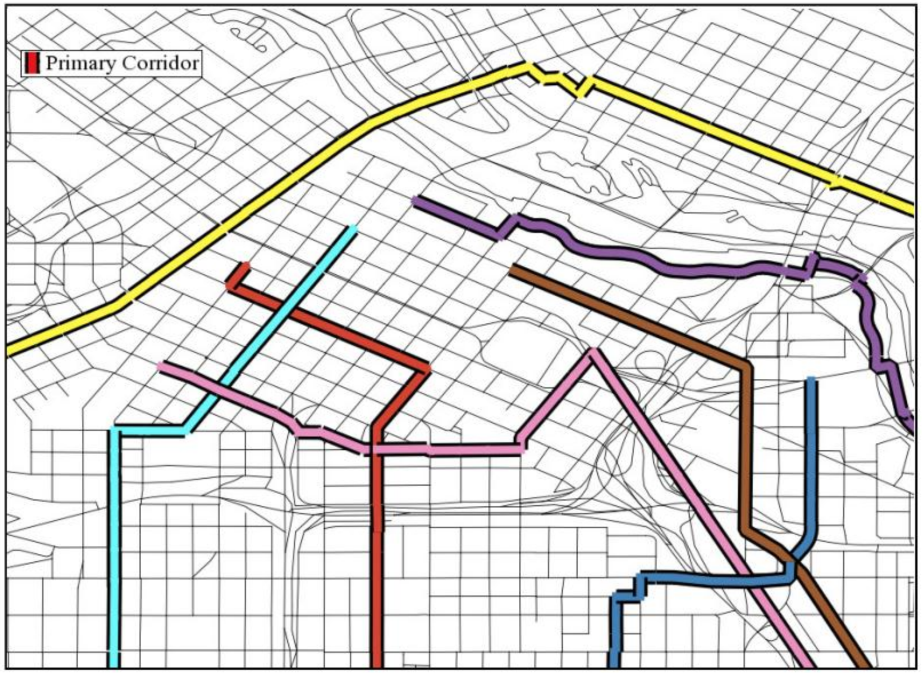
- **Primary corridor**
  - ‘Representative track of group of other tracks’ (Medoid)

- Example:

Road Network



7-Primary Corridors



Problem statement

- **Given**
  - Road Network: G = {V, E}
  - Collection of Tracks: T
  - Number k
- **Find**
  - k-Primary Corridors
- **Constraints**
  - Each **primary corridor is track** itself from set T
  - G is a connected graph with **nonnegative weights**

Solution

- <u>Input:</u> see **Given**
  1. Compute the ***track similarity matrix***

	Track 1	Track 2	Track 3
Track 1	0	1.16	3
Track 2	1.16	0	2
Track 3	3	2	0

  2. Modified k-Medoid clustering [7]

Note: <u>bottleneck</u> is the track similarity matrix computation

- Example: time comparison of steps in k-Primary Corridor problem (100 nodes/tracks, k=5)

Steps of k-PC	Runtime	Percentage
Track Similarity Matrix	46.56 sec	94.1%
Partitioning / Clustering	2.96 sec	5.9%
Total	49.52 sec	100%

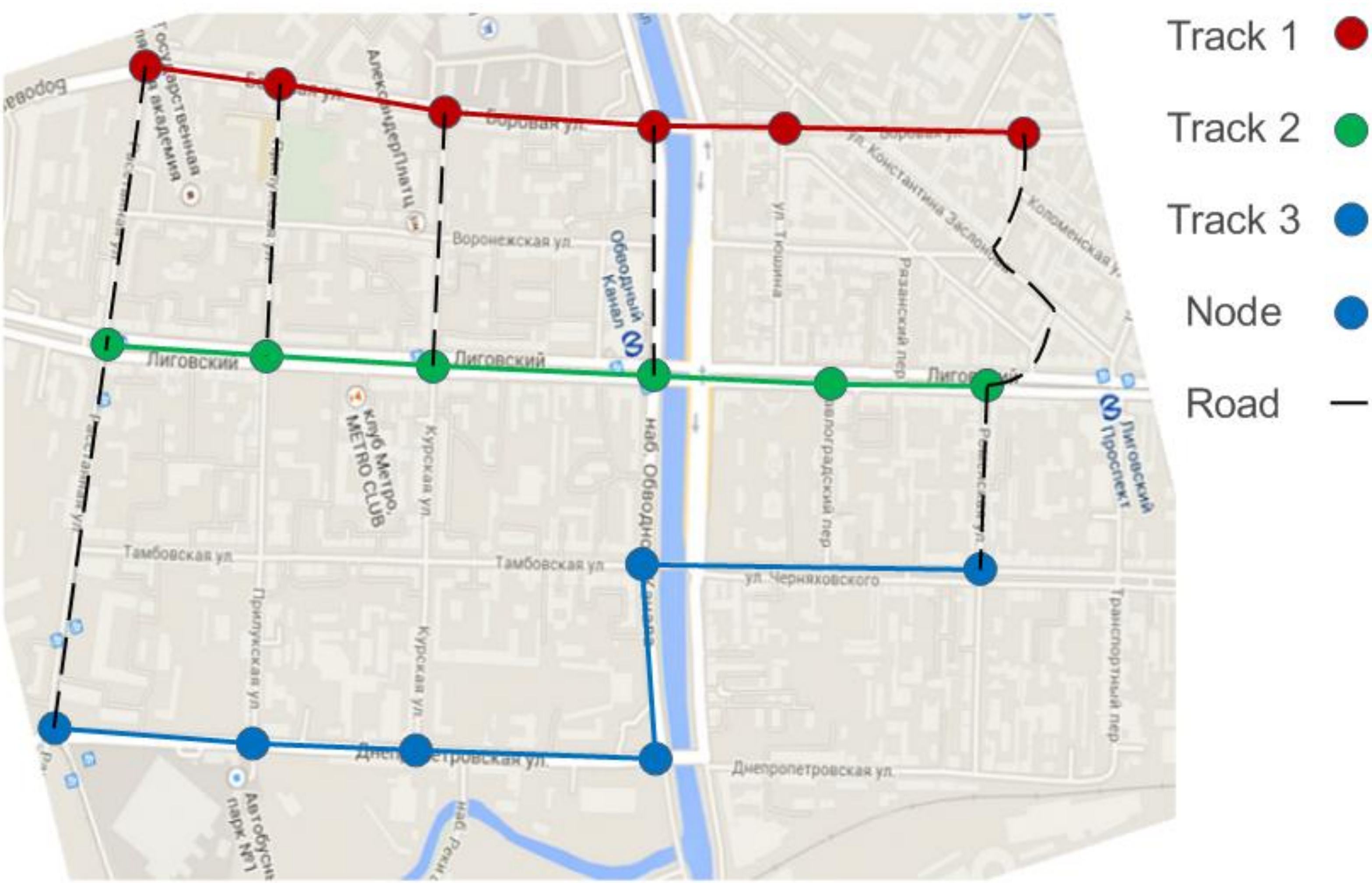
Approaches to compute the Track Similarity Matrix

– ***Graph-Node Track Similarity*** (naïve approach)

1. Consider all track pairs (t_i,t_j)
2. For each pair of nodes in tracks (t_i,t_j) run Dijkstra

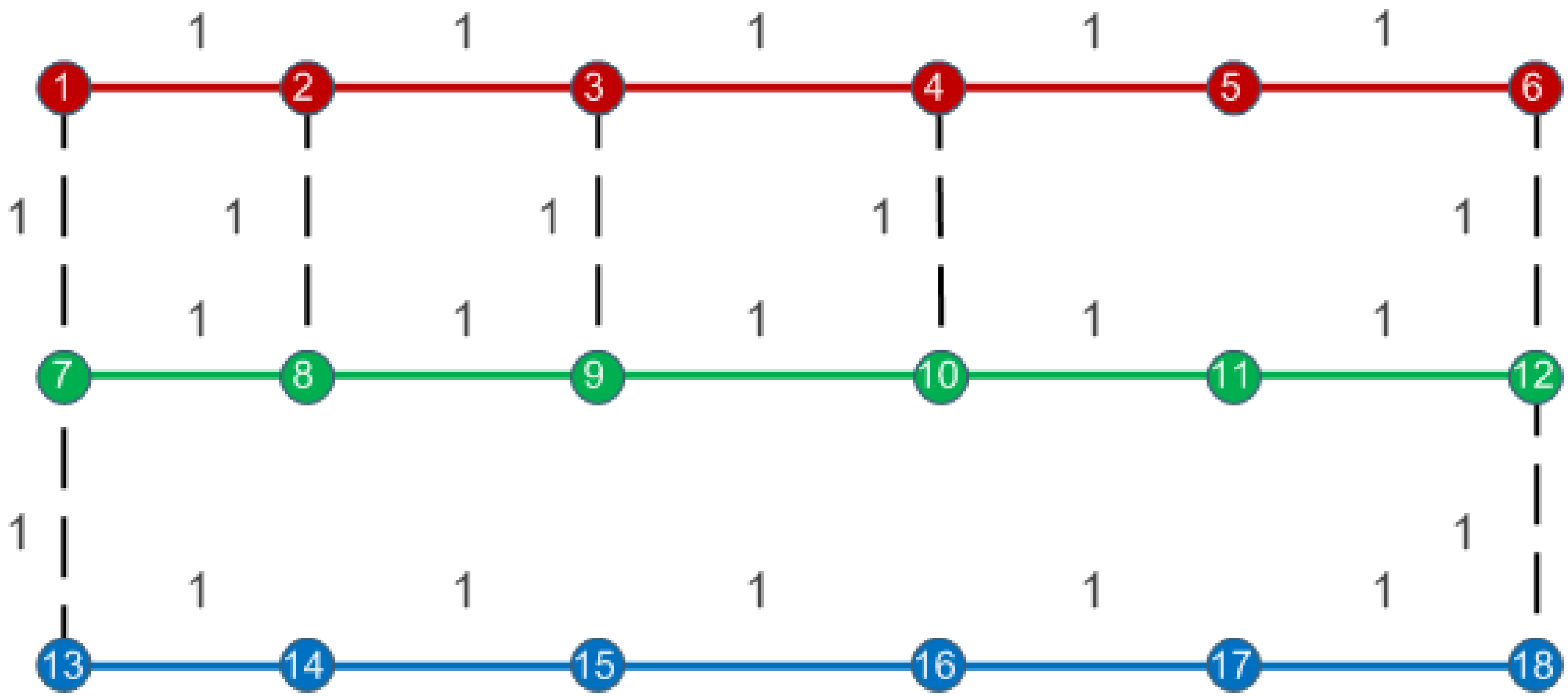
Note: $O(N^2 \cdot N^2 \cdot N \cdot \log N)$

- Example: track similarity matrix computation



- Example: track similarity matrix computation (cont.)

Transform to graph (for simplicity all weights equal 1)



- Example: track similarity matrix computation (cont.)

Calculate **track similarity function**

$$s(t_i, t_j) = \frac{1}{|t_i|} \sum_{n \in t_i} \min_{m \in t_j} \left[ShortestPath(n, m) \right]$$

n, m – nodes of tracks t_i, t_j respectively

	Track 1	Track 2	Track 3
Track 1	0	1.16	3
Track 2	1.16	0	2
Track 3	3	2	0

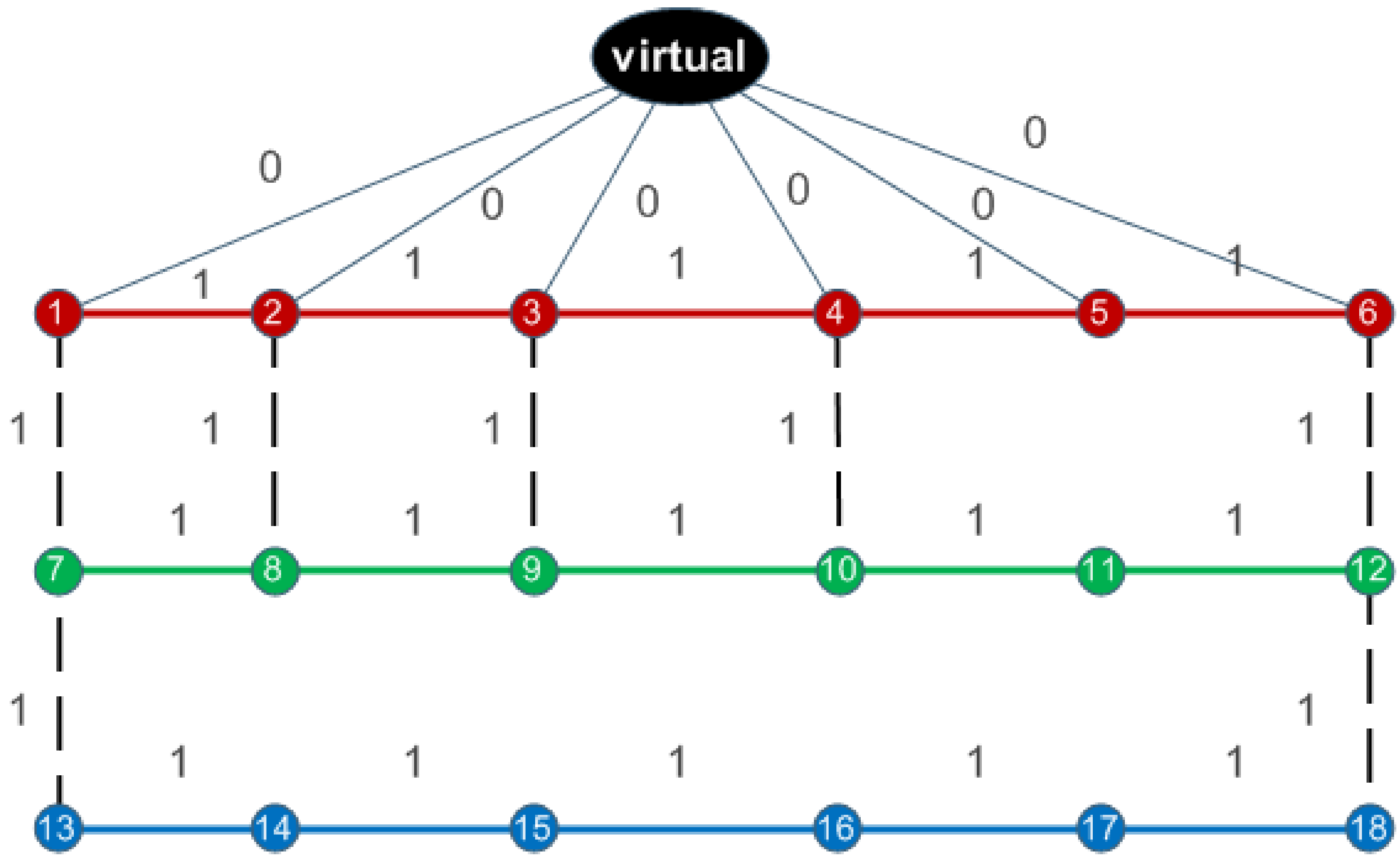
Approaches to compute the Track Similarity Matrix

– **Matrix-Element Track Similarity**

1. Consider all track pairs (i, j)
2. Attach a **virtual node** to track i
3. Run **single** Dijkstra from the virtual node to all the nodes in track j
4. Compute track similarity metric

Note: $O(N^2 \cdot N \cdot \log N)$

- Example: track similarity matrix computation



- Example: track similarity matrix computation (cont.)

Calculate **track similarity function**

$$s\left(t_i, t_j\right) = \frac{1}{\left|t_i\right|} \sum_{m \in t_j} dist[m]$$

$dist[m]$ – distance from node m in tracks $\boldsymbol{t_j}$ to its closest node in track $\boldsymbol{t_i}$

Detecting Road Intersections from GPS Traces

Alireza Fathi

John Krumm

Microsoft Research

USA

2010

Problem definition

1. **GPS data collecting**
   – Expensive:
   Specialized vehicle
   Keep up with changes in the road

   – Chip:
   Regular vehicle
   Detect road intersection

Problem definition

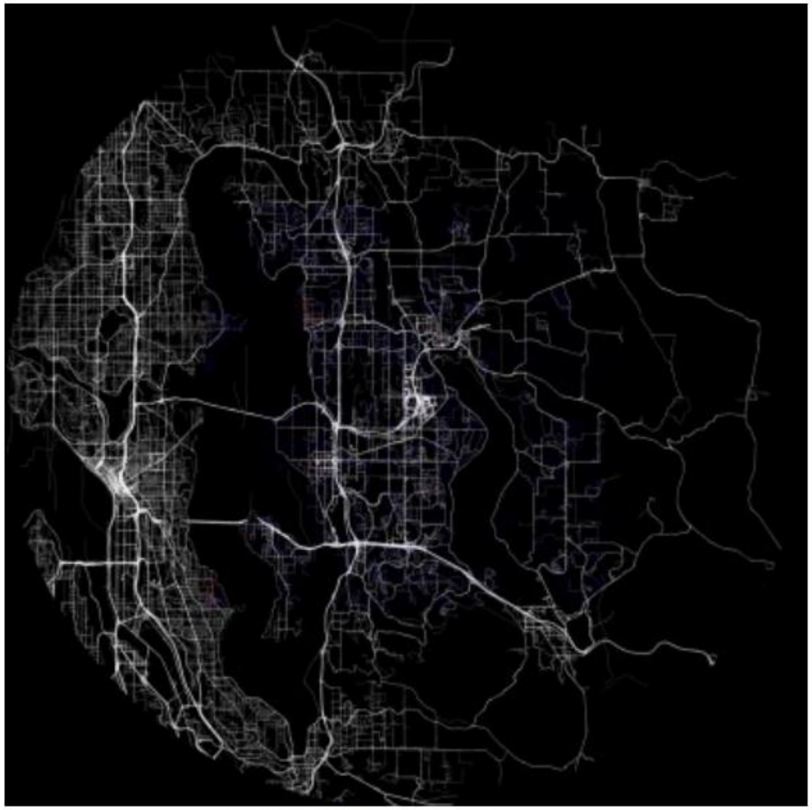
Input: GPS data of regular vehicles

2. Infer the road network from GPS traces:

- Graph G = {V, E}
- Nodes = **road intersections**

Goal: **detect road intersections**

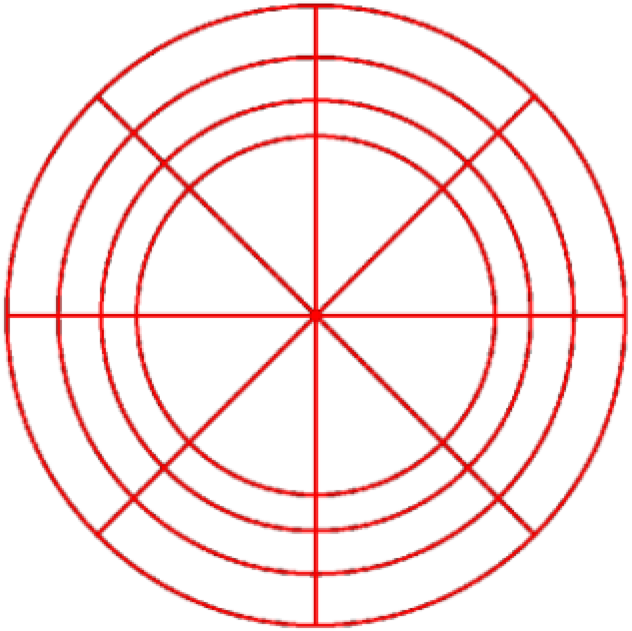
Example: GPS data of regular vehicles

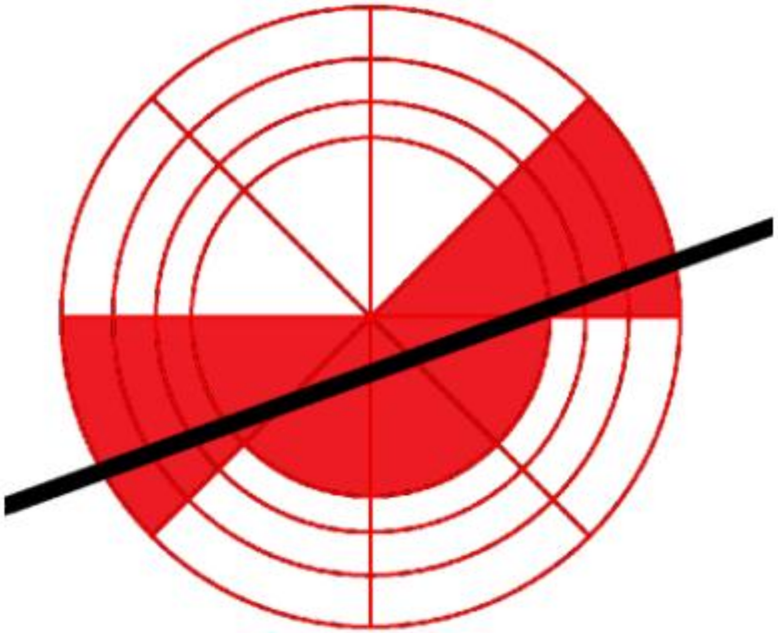


(a) all GPS data

(b) one intersection

Example: Local Shape Descriptor with 32 bins





- Sliding over GPS data to detect intersection

Training phase

Input: examples of GPS trace with intersections and non-intersections

1. Sliding by **shape descriptor** over examples
2. Map the **bins to the feature vector**
3. Learn classifier (Adaboost [8])

Example: result on test dataset

Thank you for your attention!

References

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