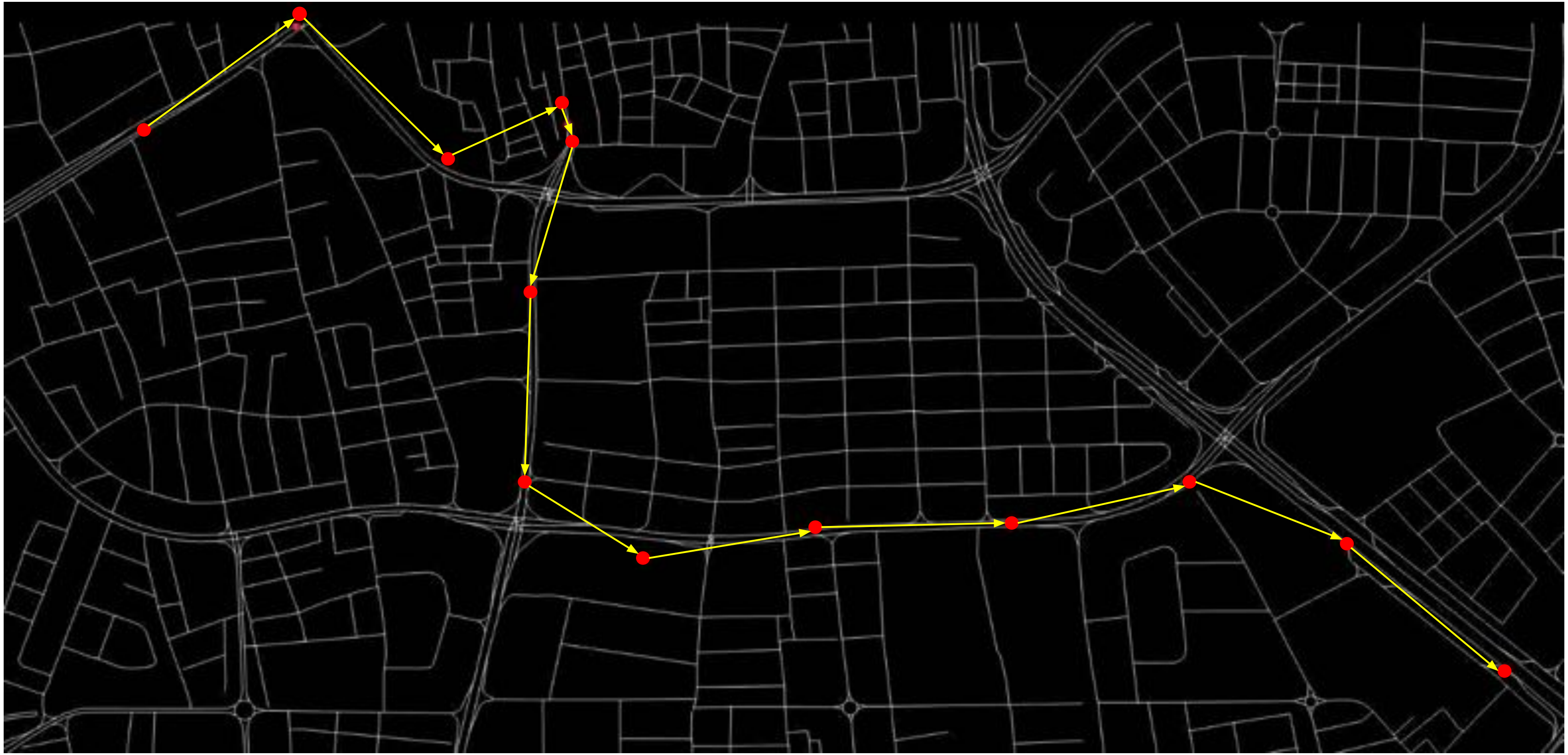
Map Inference with GPS Trajectories

What’s in a GPS trajectory?



Each observation: latitude/longitude, heading, speed

What can we infer from GPS trajectories?

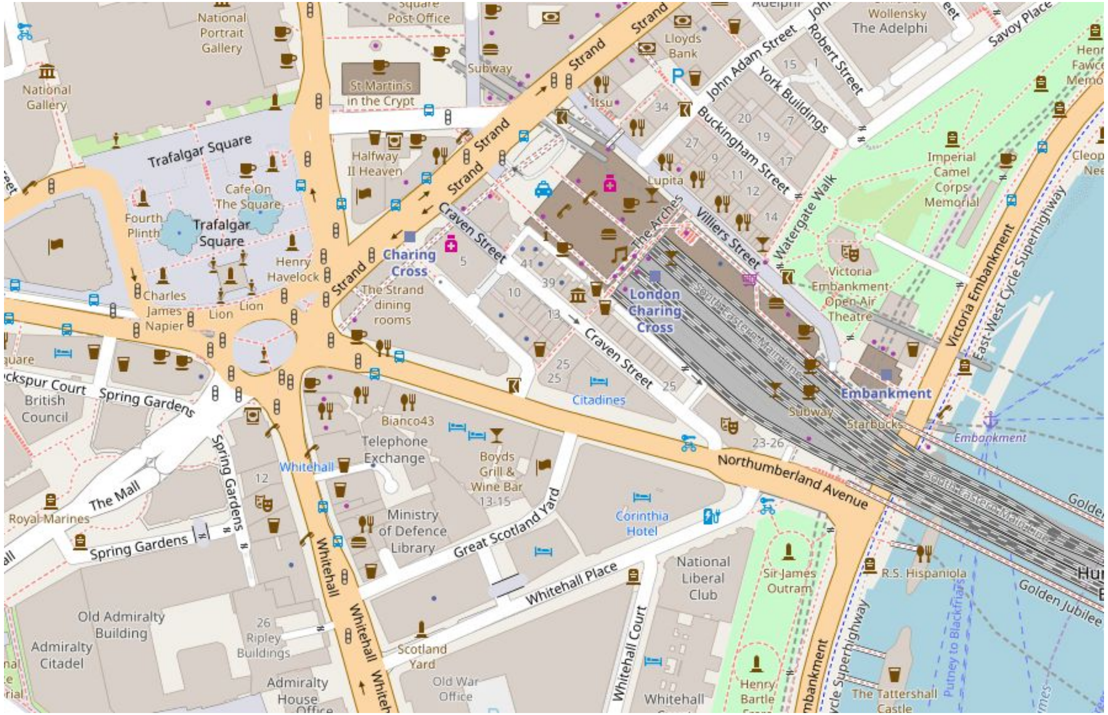
- Road topology
- Typical speeds
- Road directionality

Real-time:

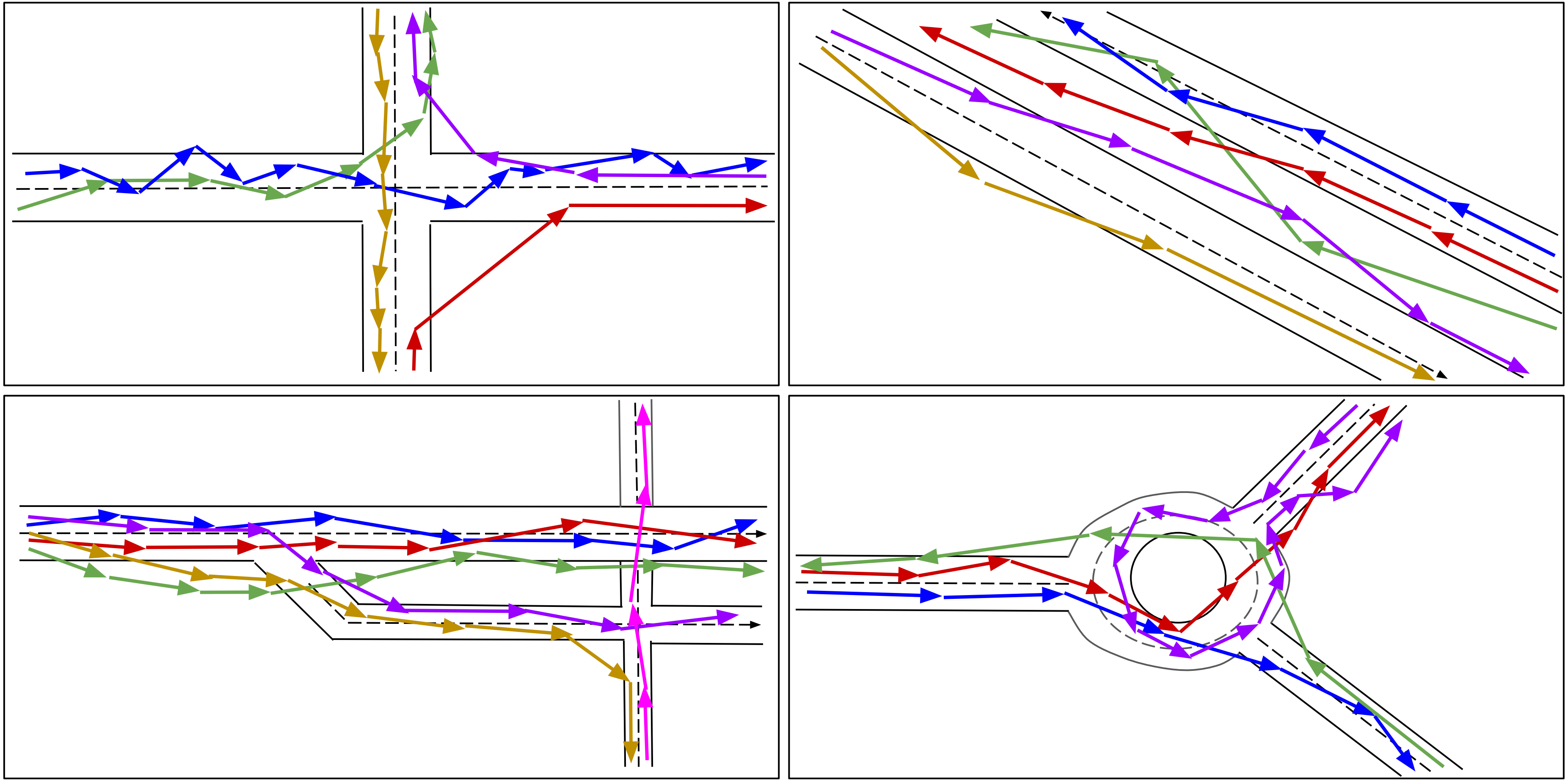
- Road closures
- Congestion

Maybe also predictions for:

- Stop signs / signal lights
- Speed limits
- Turn restrictions
- Number of lanes
- Road type (motorway, primary/avenue, residential/street)



Inferring Road Topology: Noise, Sparsity, Complexity

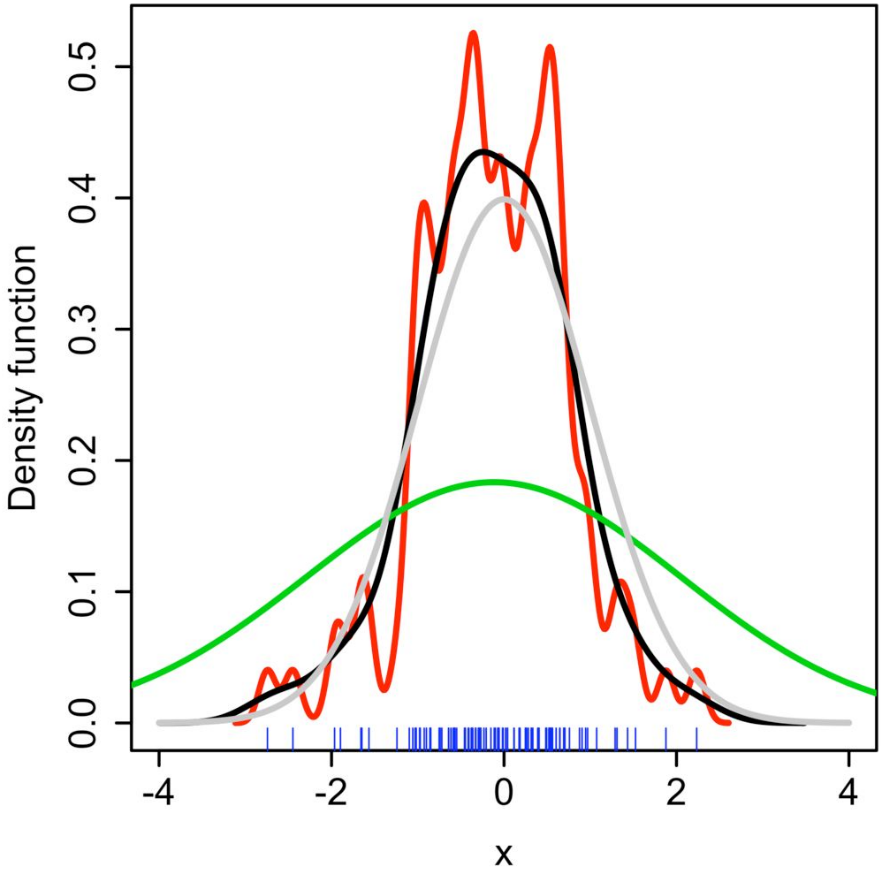


Inferring Road Topology

Traditional Approaches:

- Kernel Density Estimation
- Clustering
- Trajectory Merging

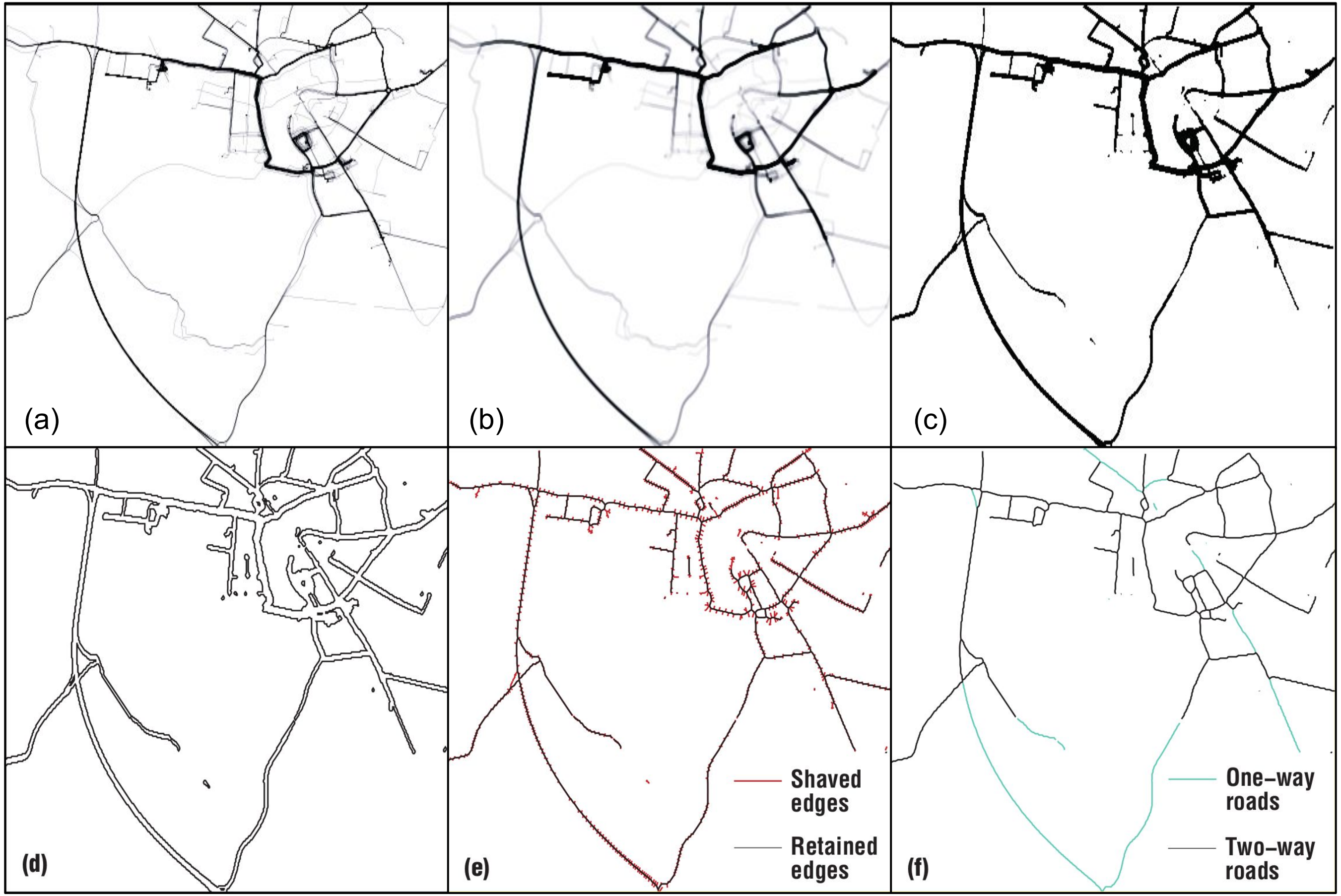
Inferring Road Topology: Kernel Density Estimation



- Grey: a normal distribution
- Blue: points sampled from this distribution
- Red, black: two kernel density estimates that smooth the sampled points

Jonathan Davies, Alastair Beresford, and Andy Hopper. "Scalable, distributed, real-time map generation" in *IEEE Pervasive Computing* (2006).

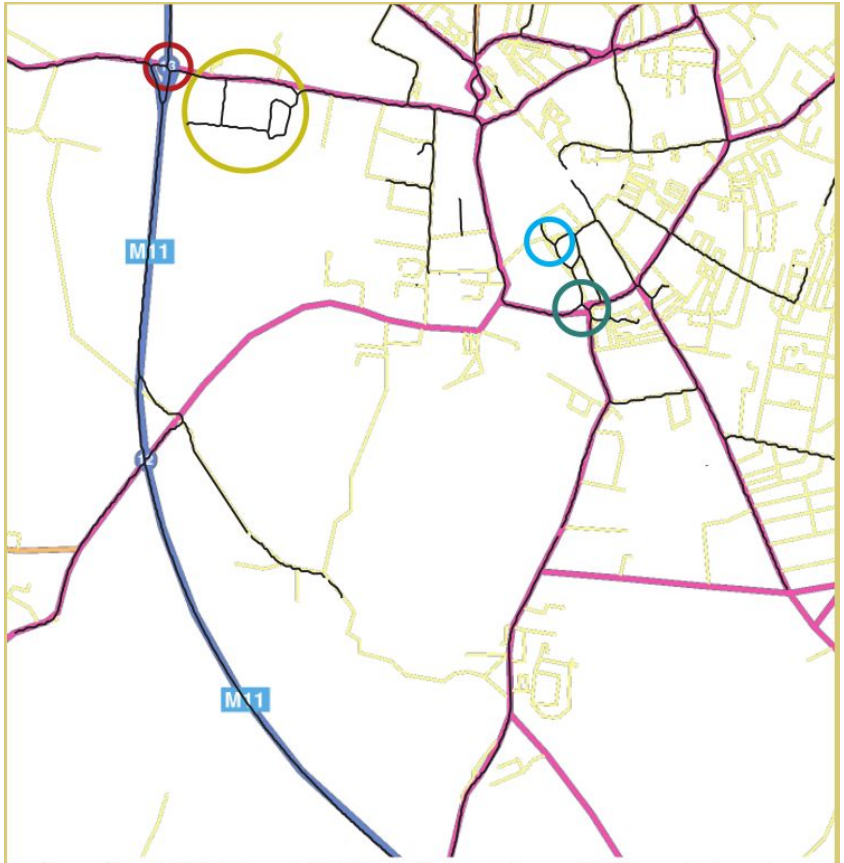
Inferring Road Topology: Kernel Density Estimation



(a) 2D histogram
(b) blurred histogram
(c) thresholded histogram
(d) contours
(e) Voronoi graph
(f) extracted graph

Jonathan Davies, Alastair Beresford, and Andy Hopper. “Scalable, distributed, real-time map generation” in *IEEE Pervasive Computing* (2006).

Inferring Road Topology: Kernel Density Estimation



Yellow, purple, blue wide lines: existing map
Black lines: roads inferred by KDE

Circles:

- Gold: new inferred roads
- Red: bridge misinterpreted as junction
- Blue: misaligned junction
- Green: two junctions merged into one

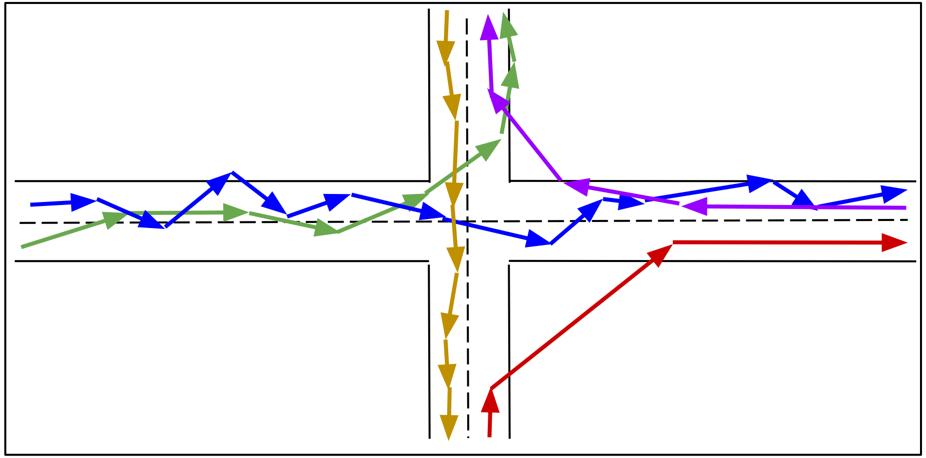
Jonathan Davies, Alastair Beresford, and Andy Hopper. “Scalable, distributed, real-time map generation” in *IEEE Pervasive Computing* (2006).

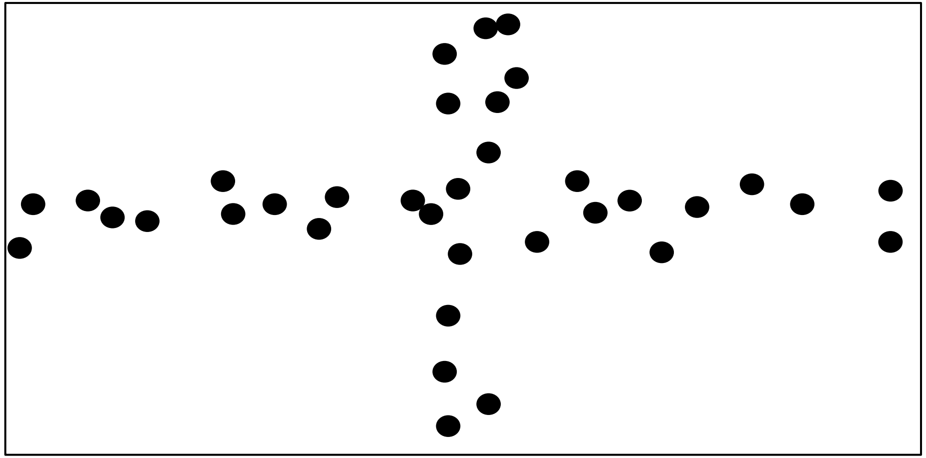
Inferring Road Topology: Kernel Density Estimation

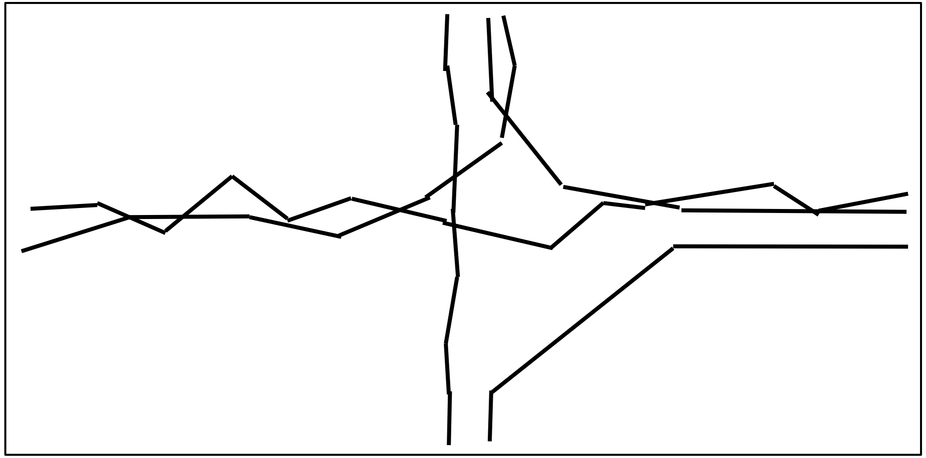
Parameters:

- Cell size
- Blur factor (sigma)
- Masking threshold
- Histogram: points versus lines

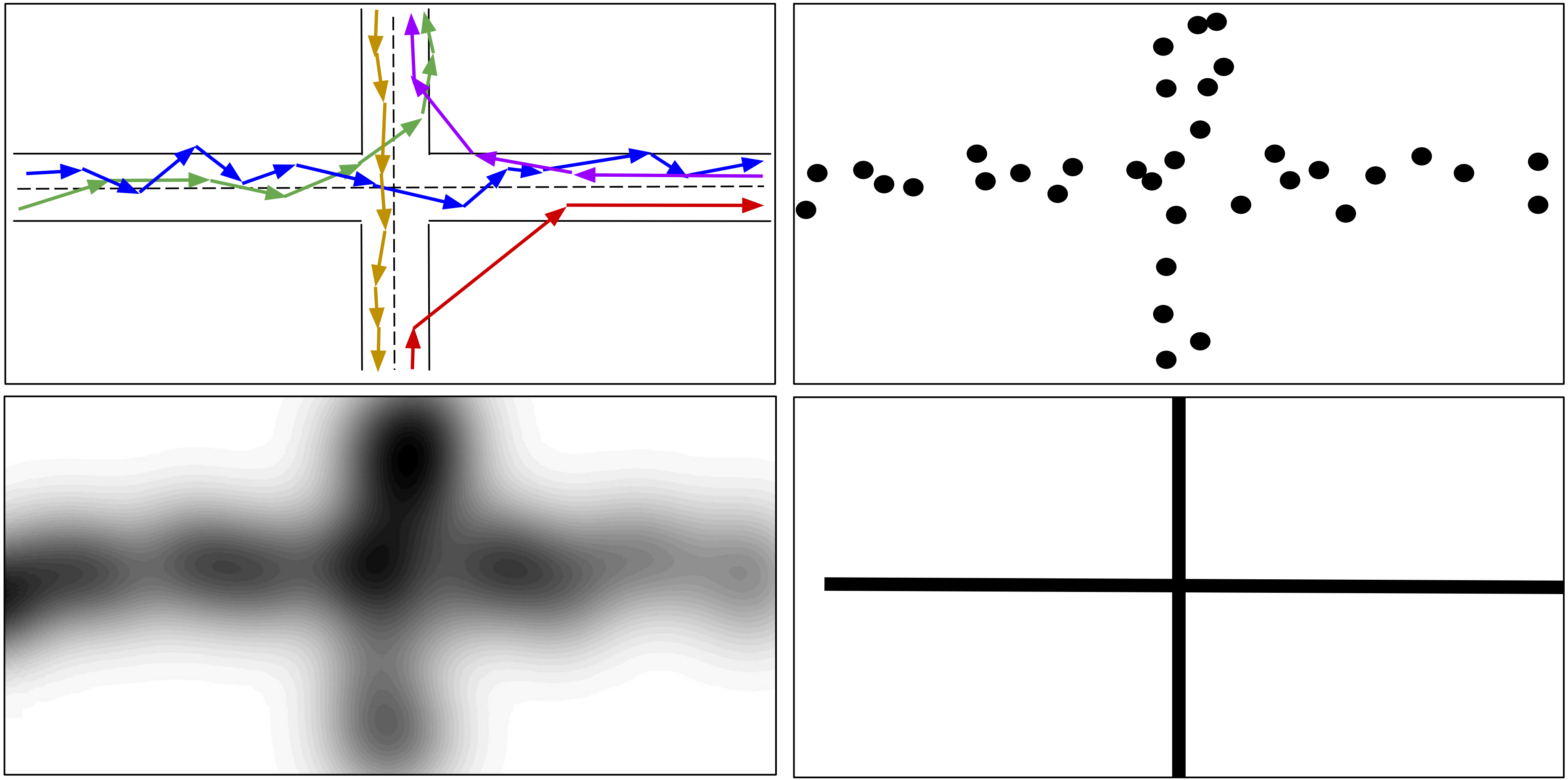
Inferring Road Topology: Kernel Density Estimation



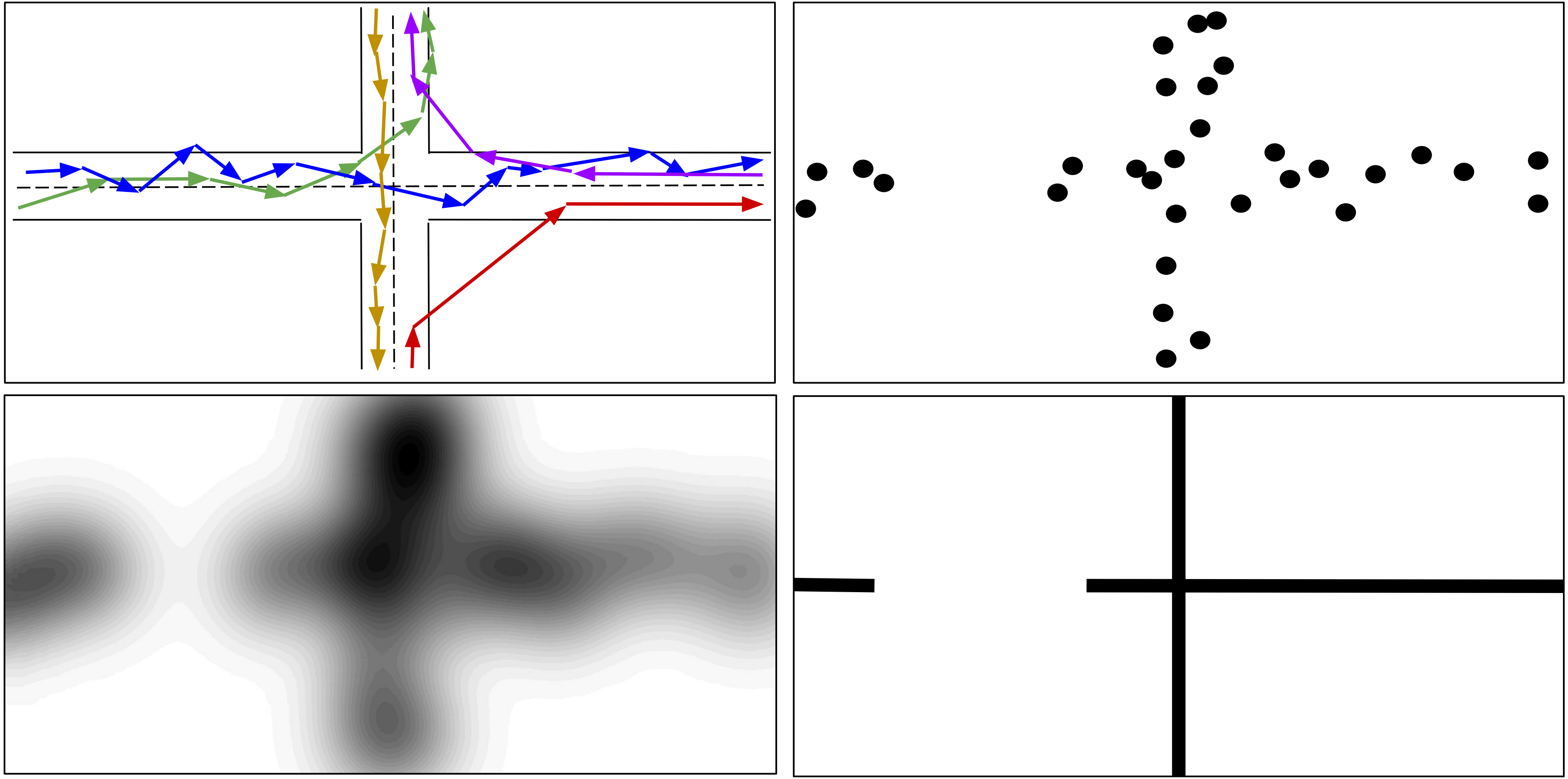




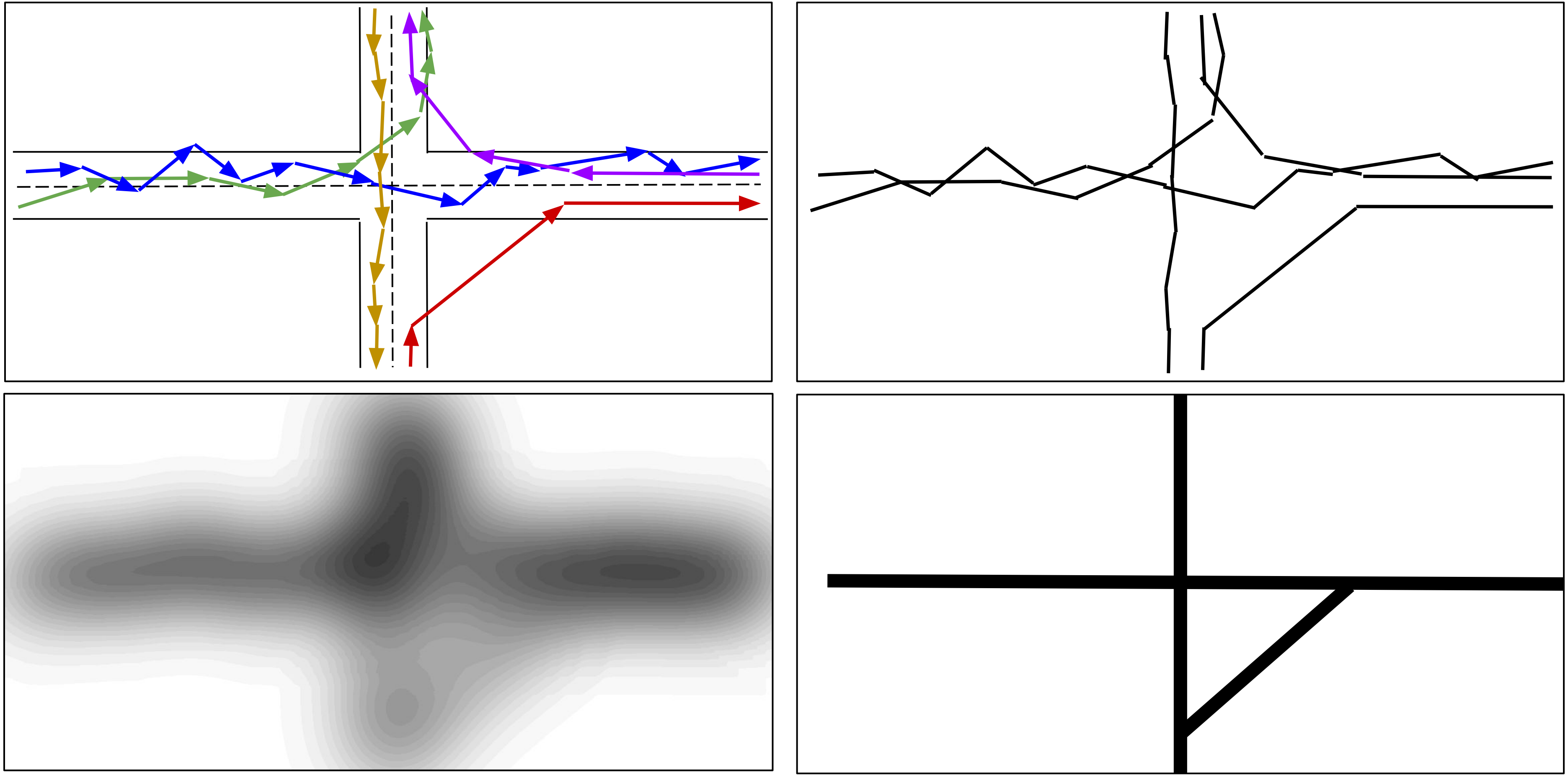
Inferring Road Topology: Kernel Density Estimation



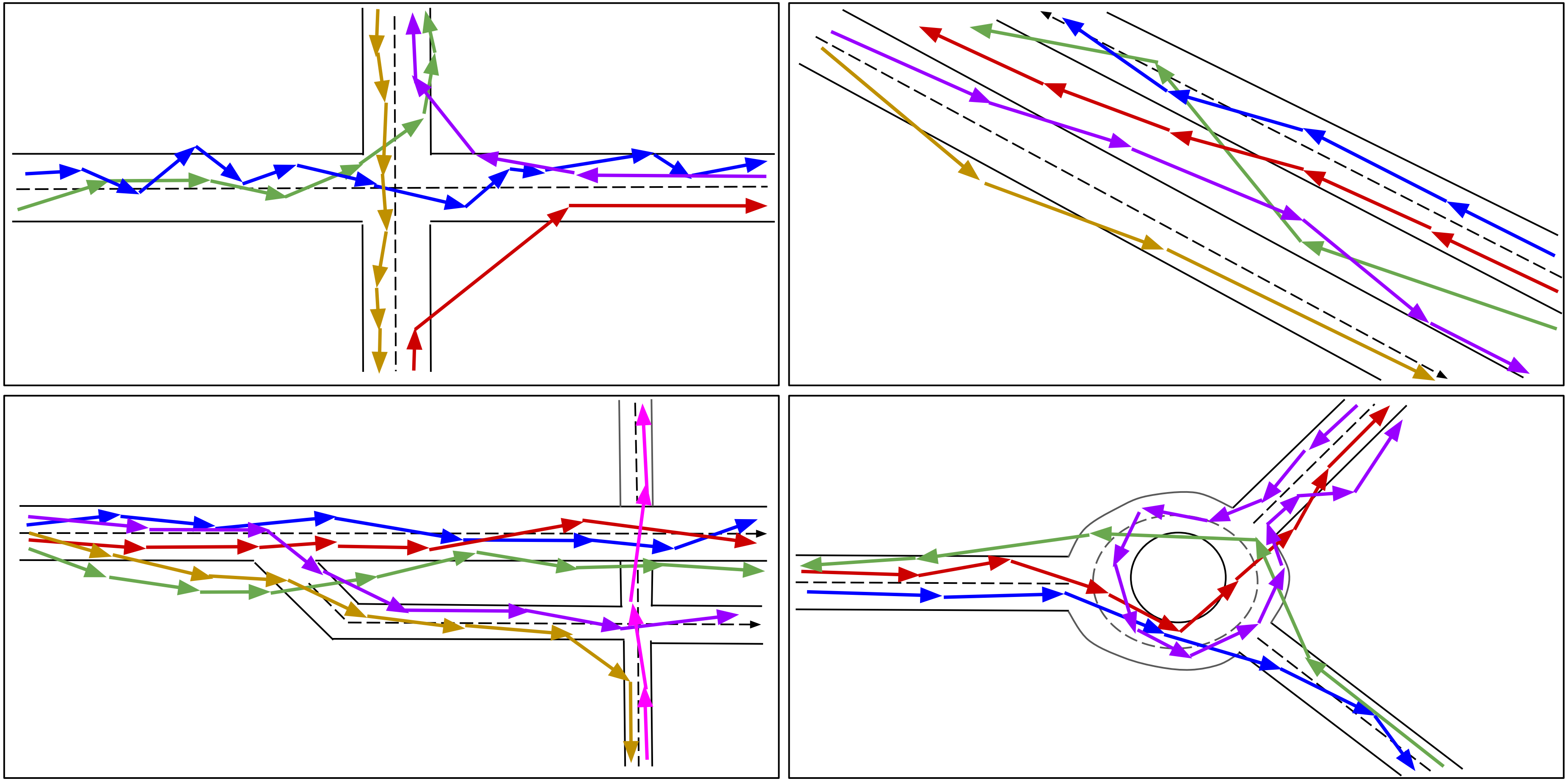
Inferring Road Topology: Kernel Density Estimation



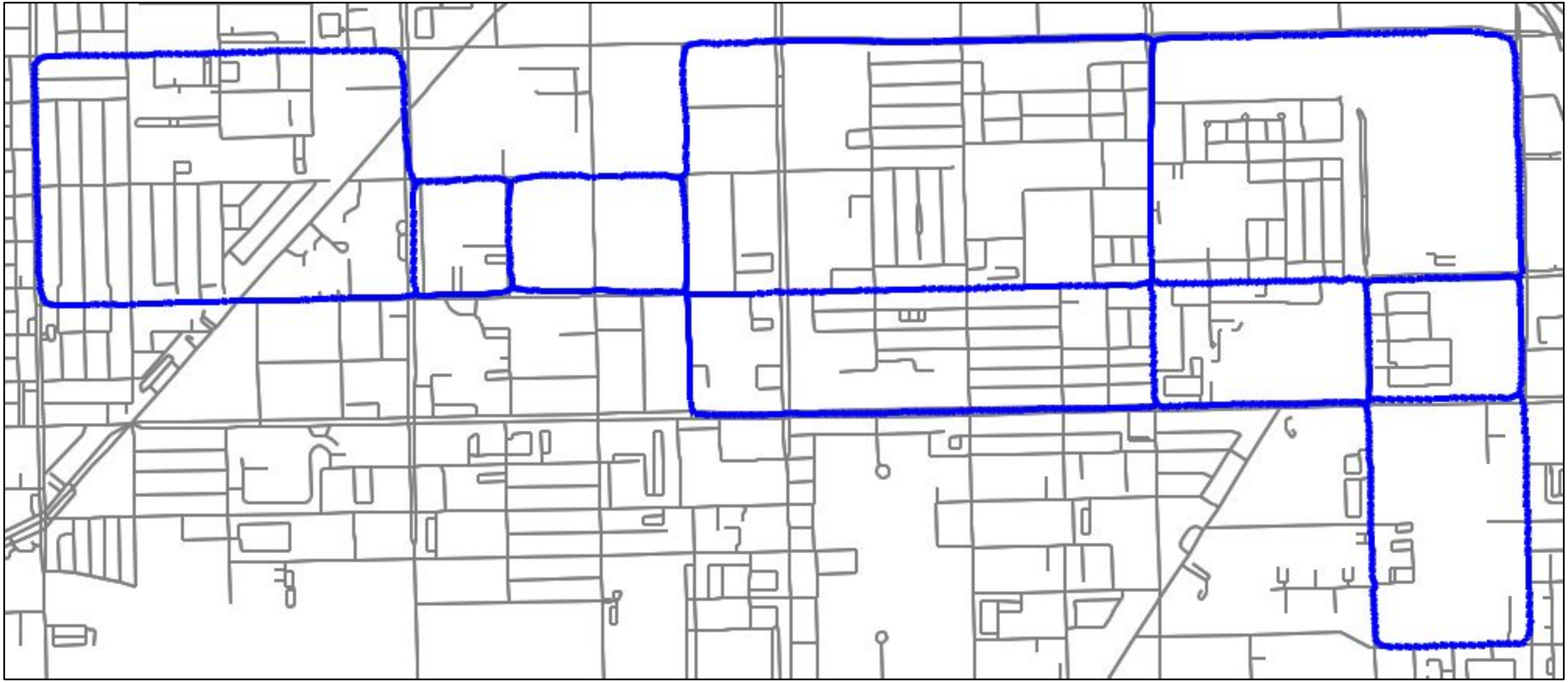
Inferring Road Topology: Kernel Density Estimation



Inferring Road Topology: Kernel Density Estimation



Inferring Road Topology: Kernel Density Estimation



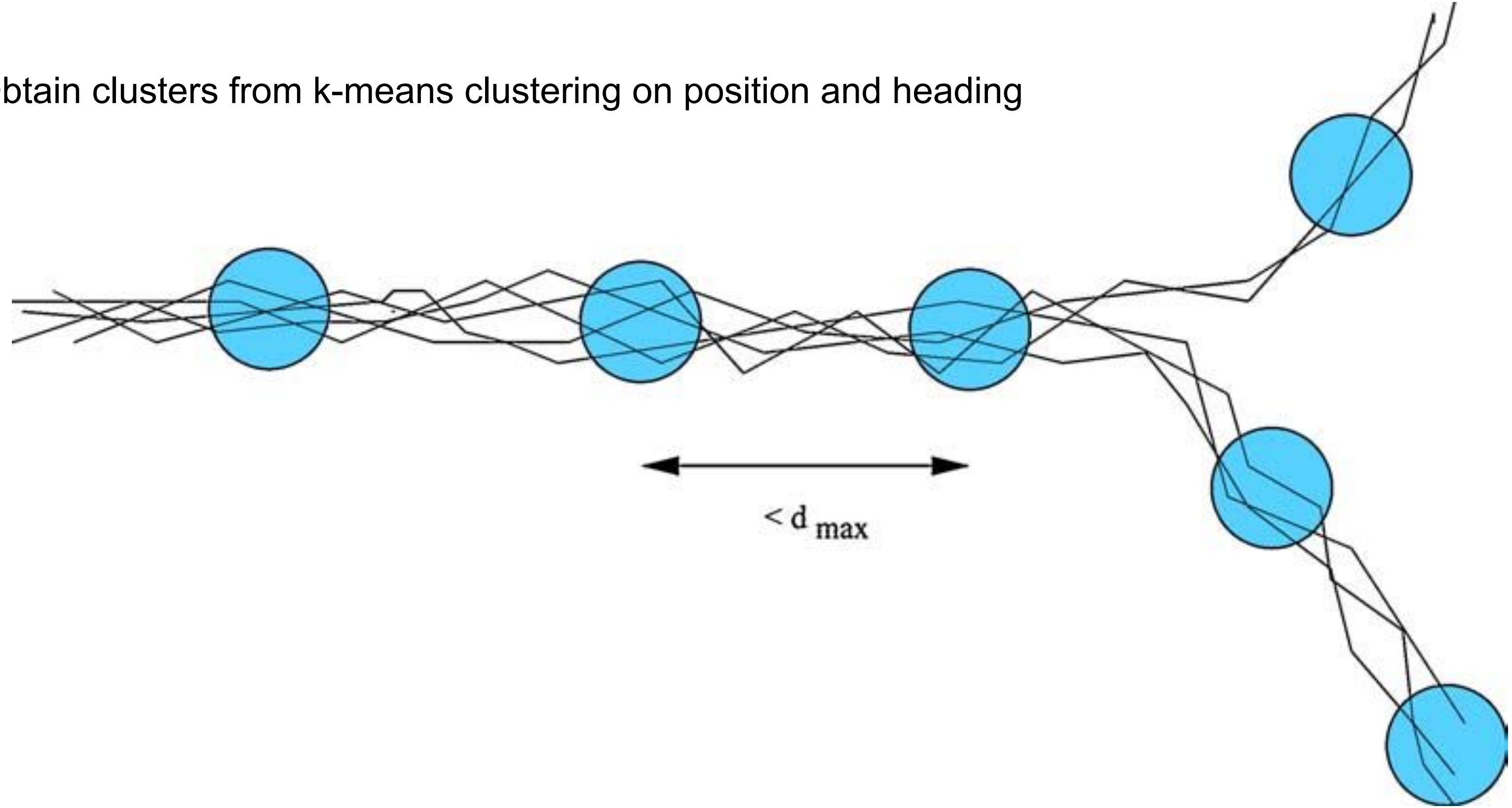
Inferring Road Topology

Traditional Approaches:

- Kernel Density Estimation
- Clustering
- Trajectory Merging

Inferring Road Topology: Clustering

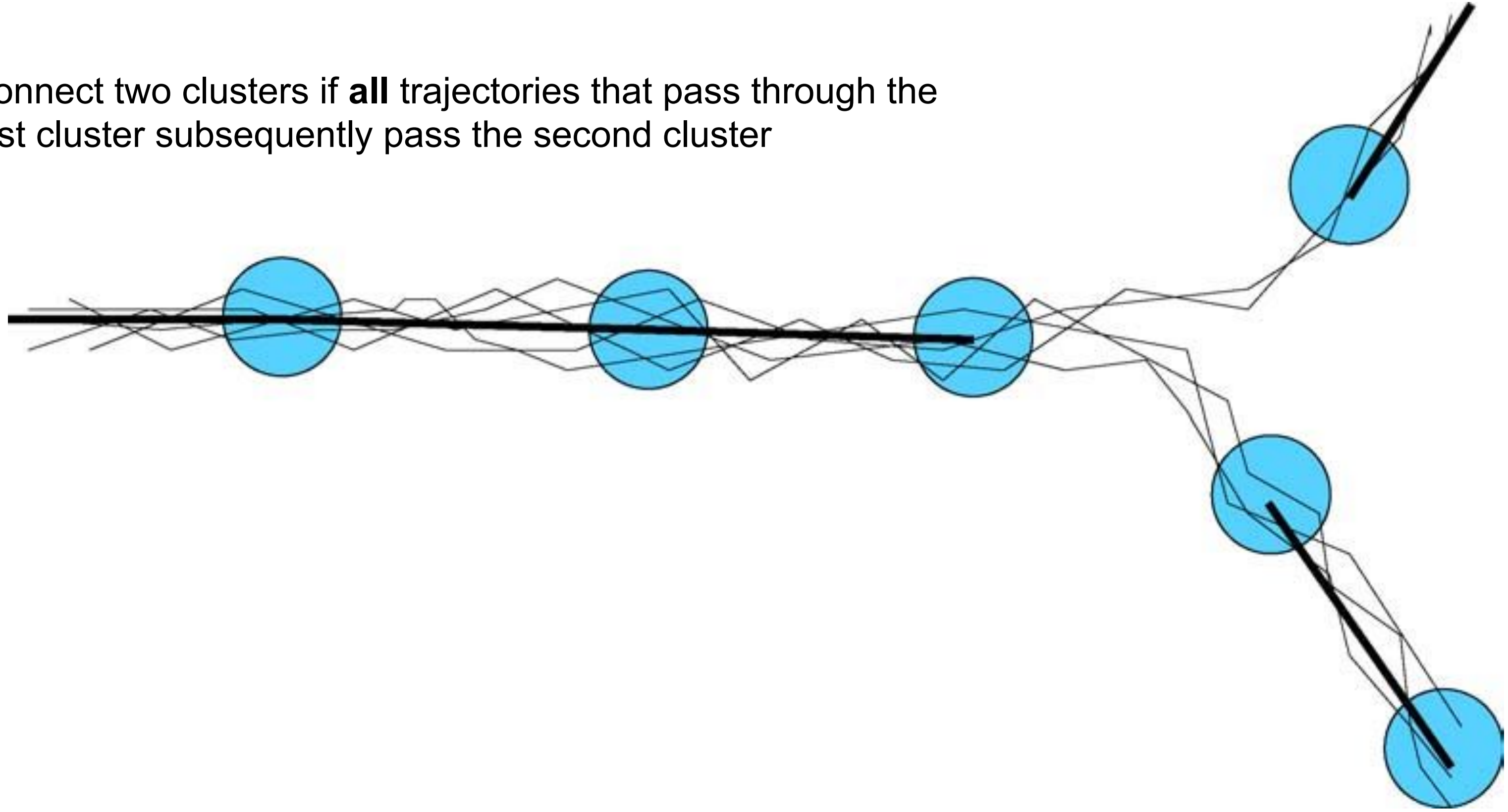
Obtain clusters from k-means clustering on position and heading



Stefan Schroedl, Kiri Wagstaff et al. “Mining GPS Traces for Map Refinement” in *Data Mining and Knowledge Discovery* (2004).

Inferring Road Topology: Clustering

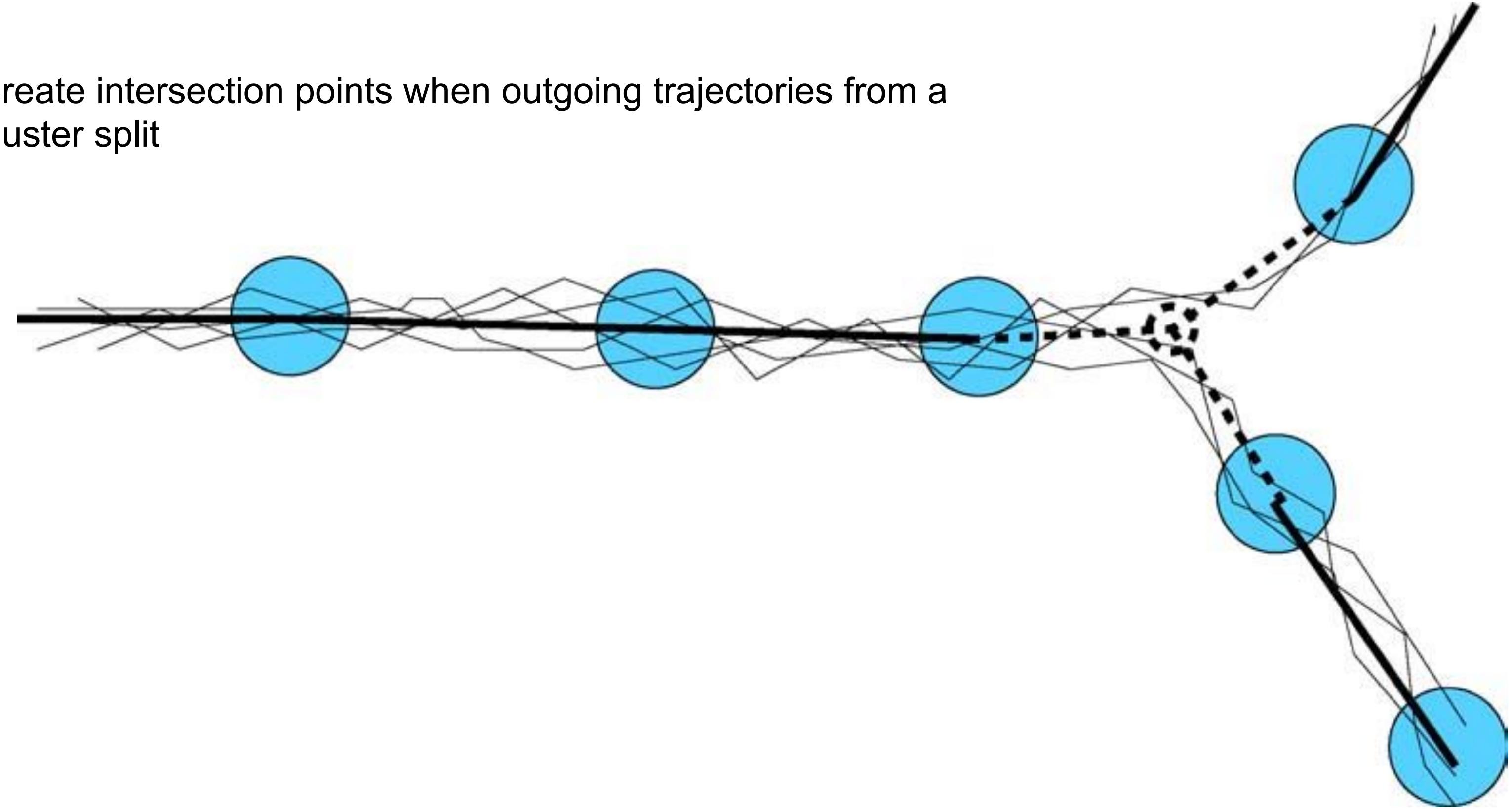
Connect two clusters if **all** trajectories that pass through the first cluster subsequently pass the second cluster



Stefan Schroedl, Kiri Wagstaff et al. “Mining GPS Traces for Map Refinement” in *Data Mining and Knowledge Discovery* (2004).

Inferring Road Topology: Clustering

Create intersection points when outgoing trajectories from a cluster split



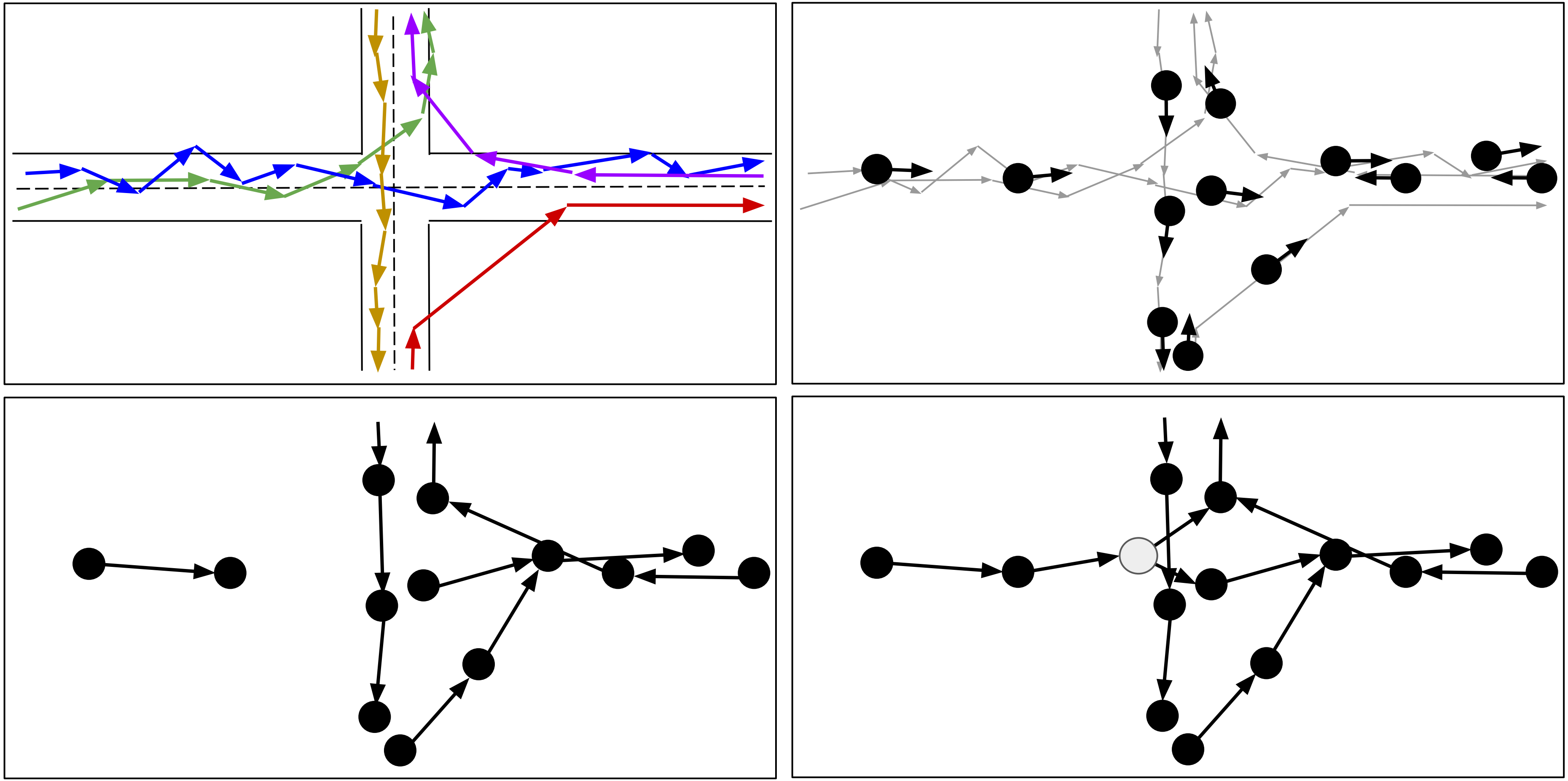
Stefan Schroedl, Kiri Wagstaff et al. “Mining GPS Traces for Map Refinement” in *Data Mining and Knowledge Discovery* (2004).

Inferring Road Topology: Clustering

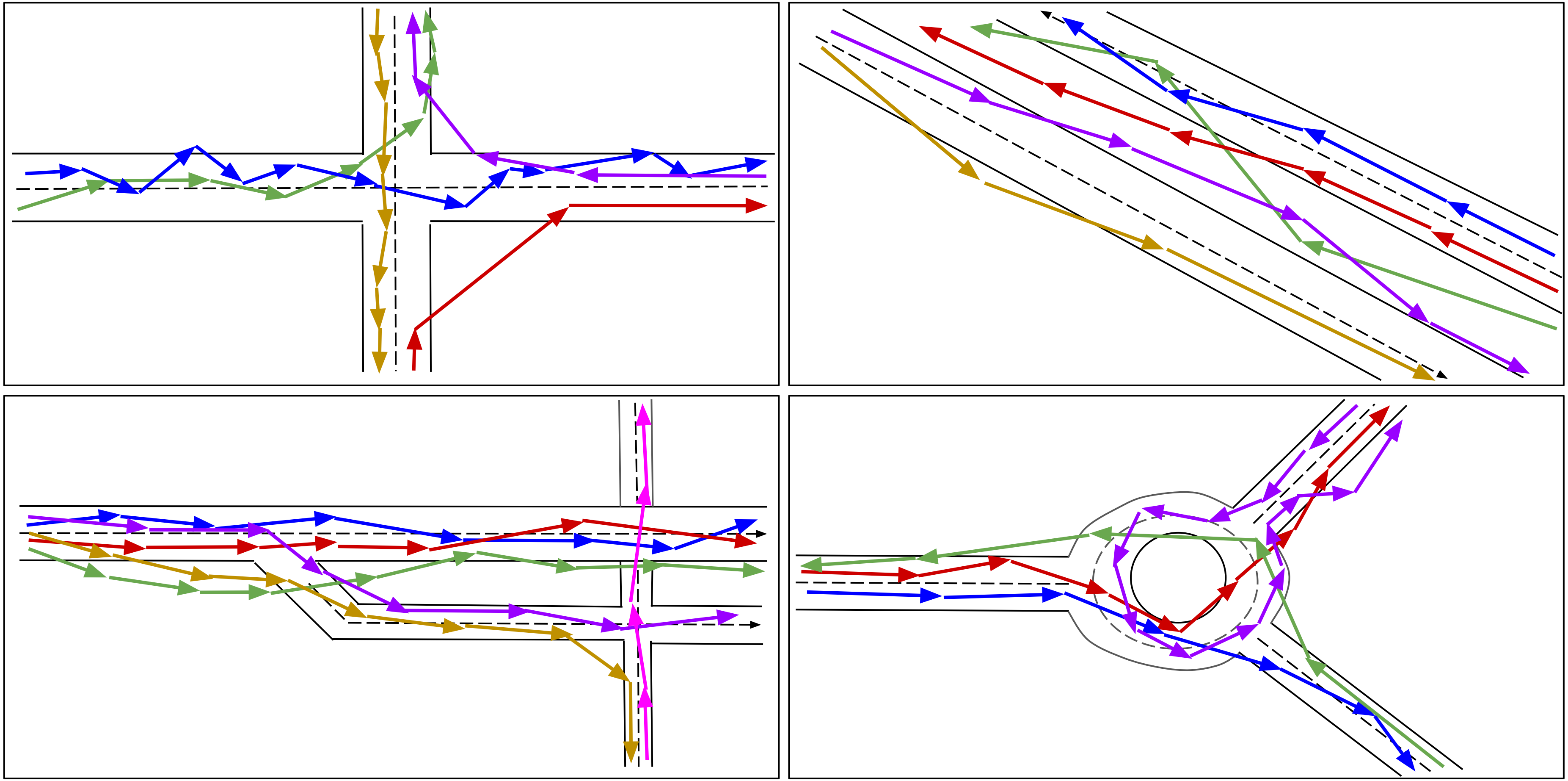
Parameters:

- Number of clusters / distance between clusters
- How to connect clusters together?
- Should we adjust cluster positions after connecting them?

Inferring Road Topology: Clustering



Inferring Road Topology: Clustering



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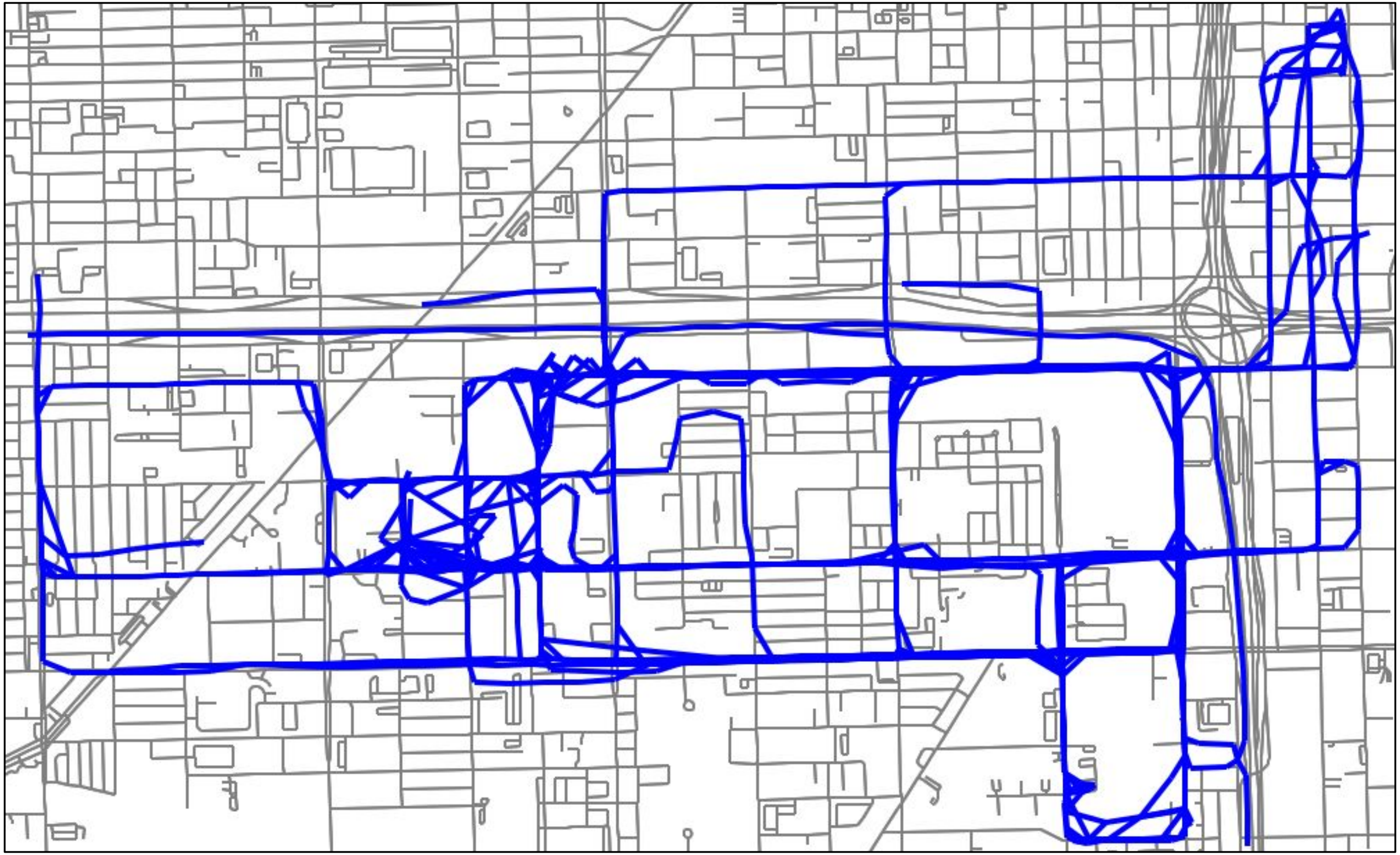

Inferring Road Topology

Traditional Approaches:

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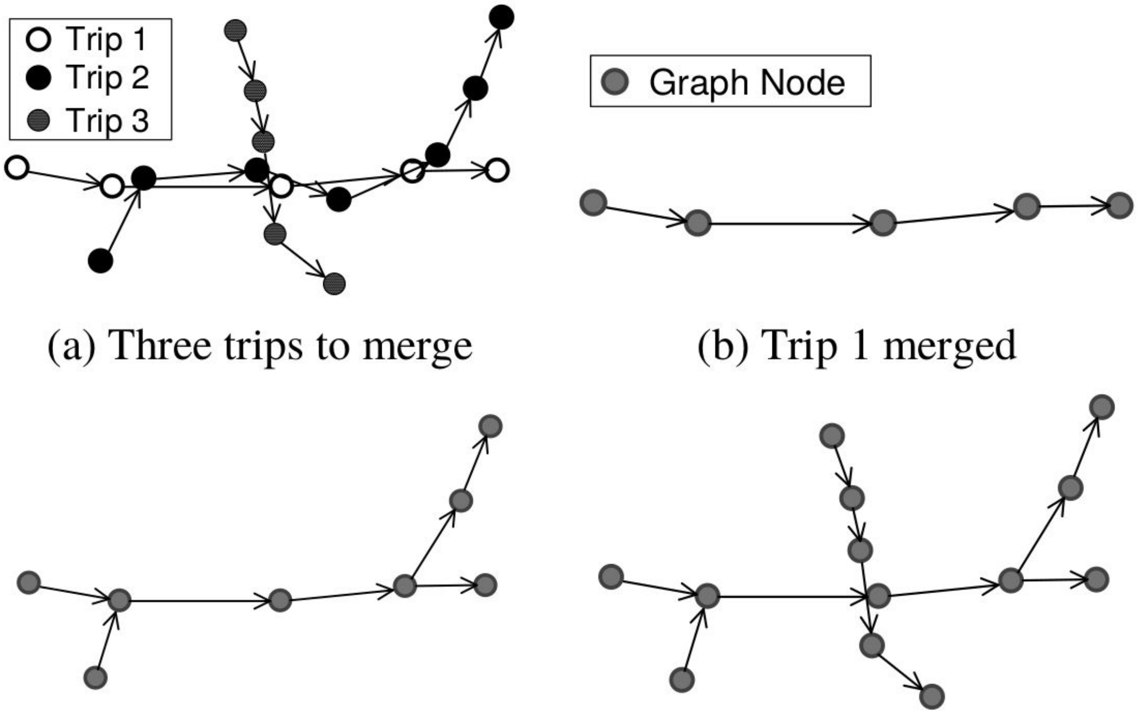
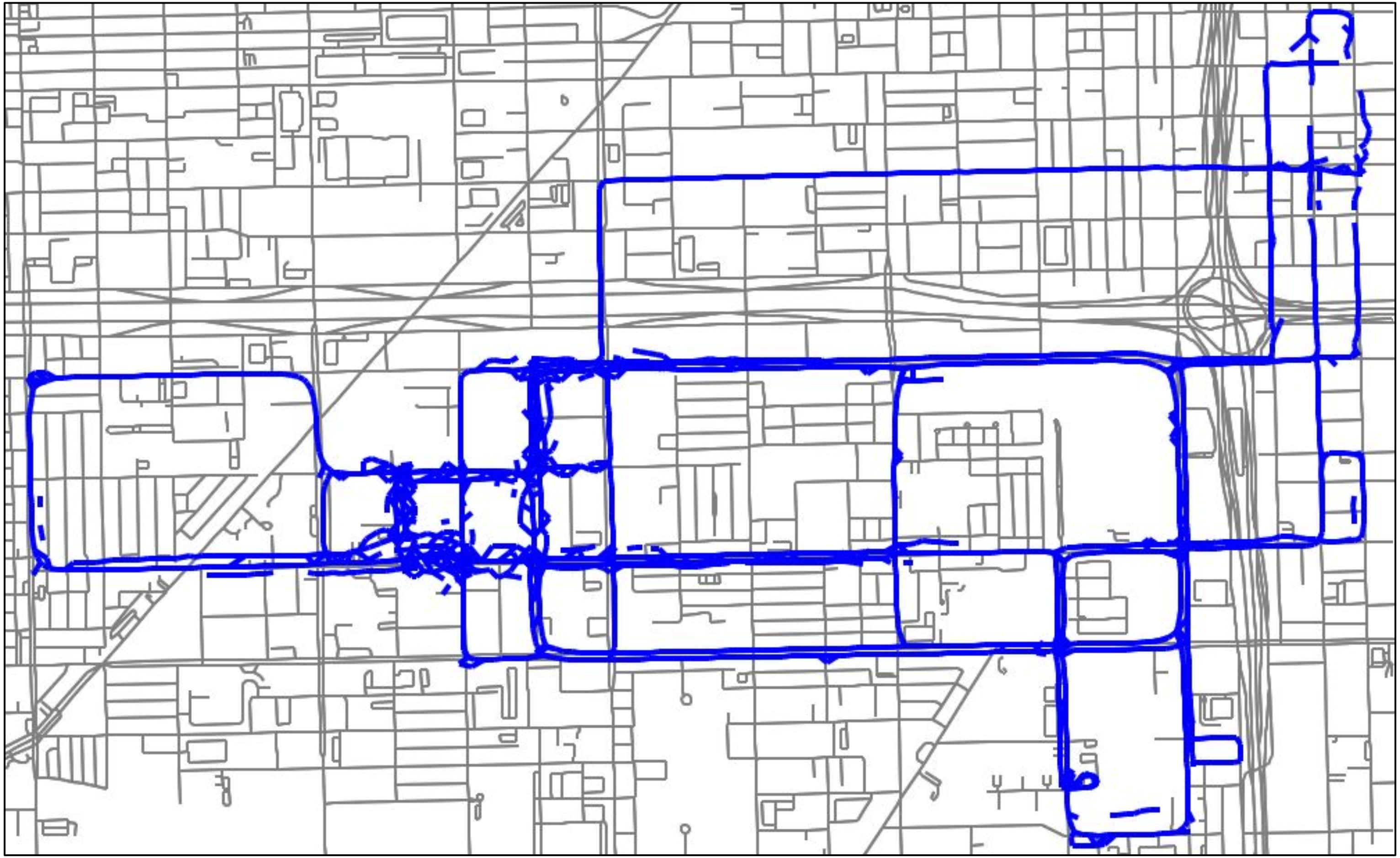
Inferring Road Topology: Trajectory Merging



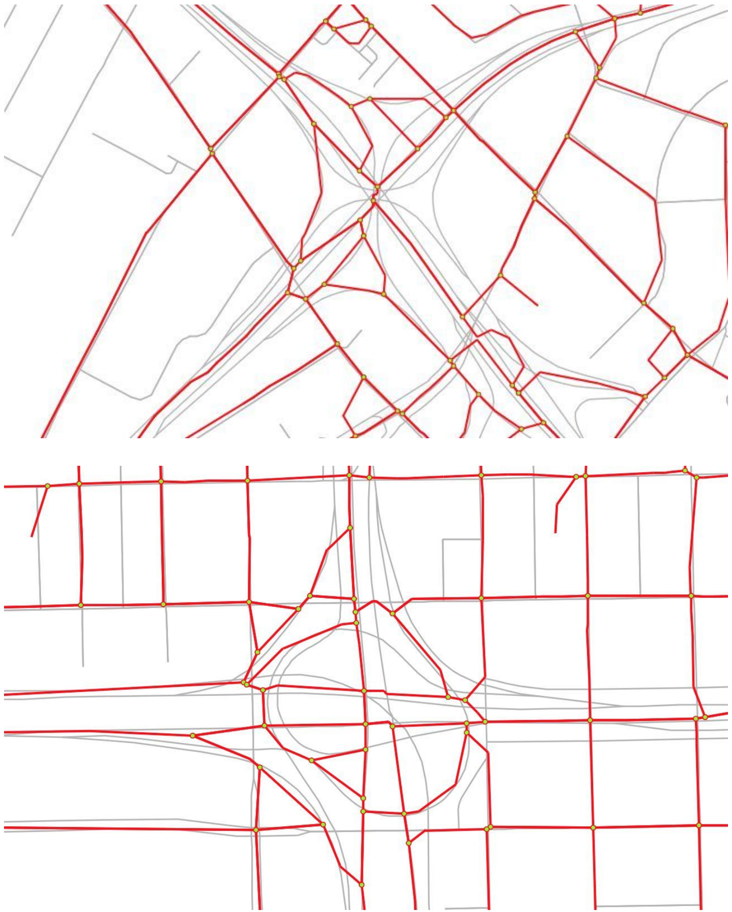
(a) Three trips to merge (b) Trip 1 merged (c) Trip 2 merged (d) All trips merged

Lili Cao and John Krumm. “From GPS Traces to a Routable Road Map” in ACM SIGSPATIAL (2009).

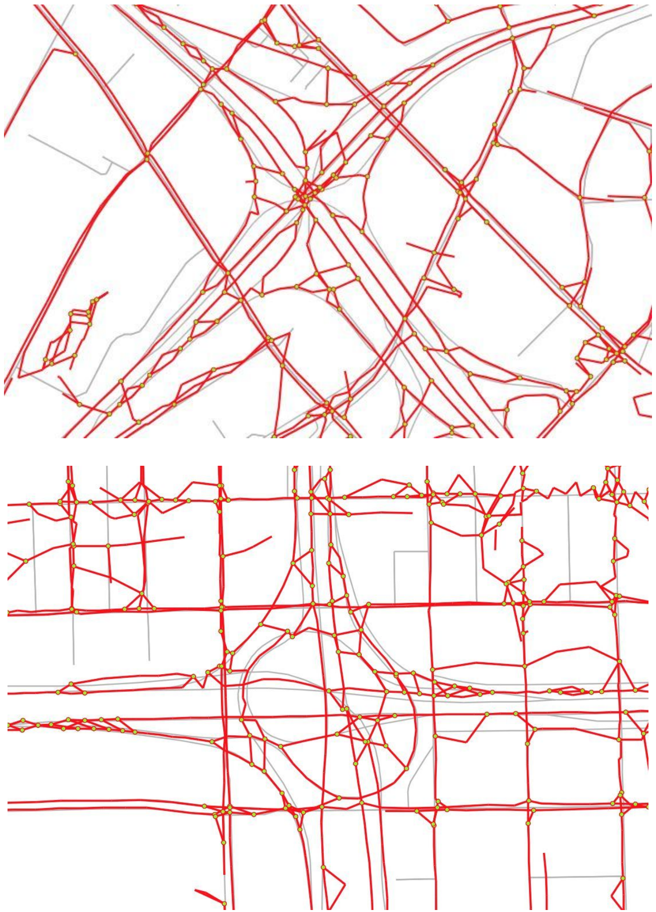
Inferring Road Topology: Trajectory Merging



Inferring Road Topology: Challenges

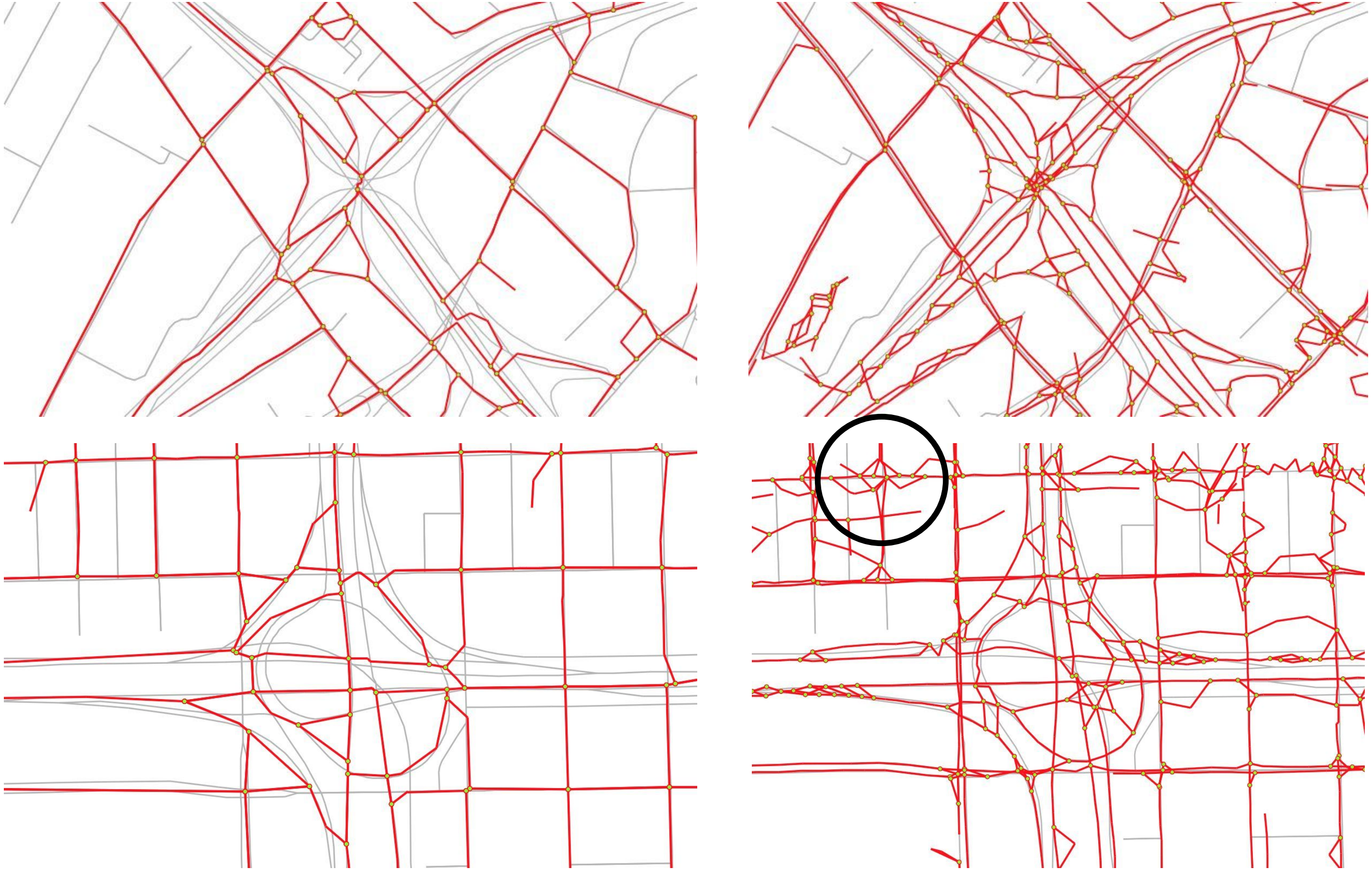


Kernel Density Estimation



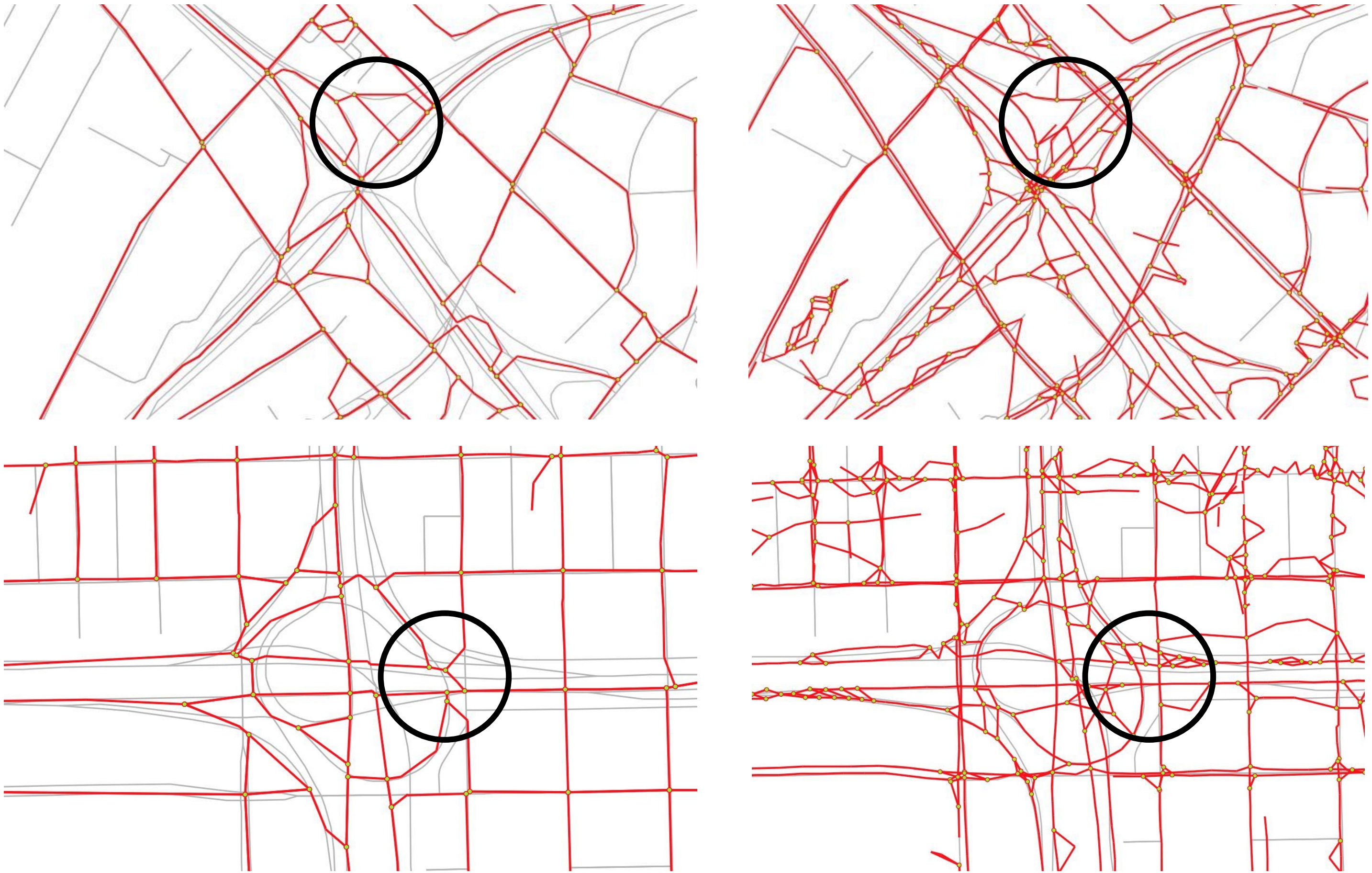
Clustering

Inferring Road Topology: Challenges



Kernel Density Estimation | Clustering

Inferring Road Topology: Challenges



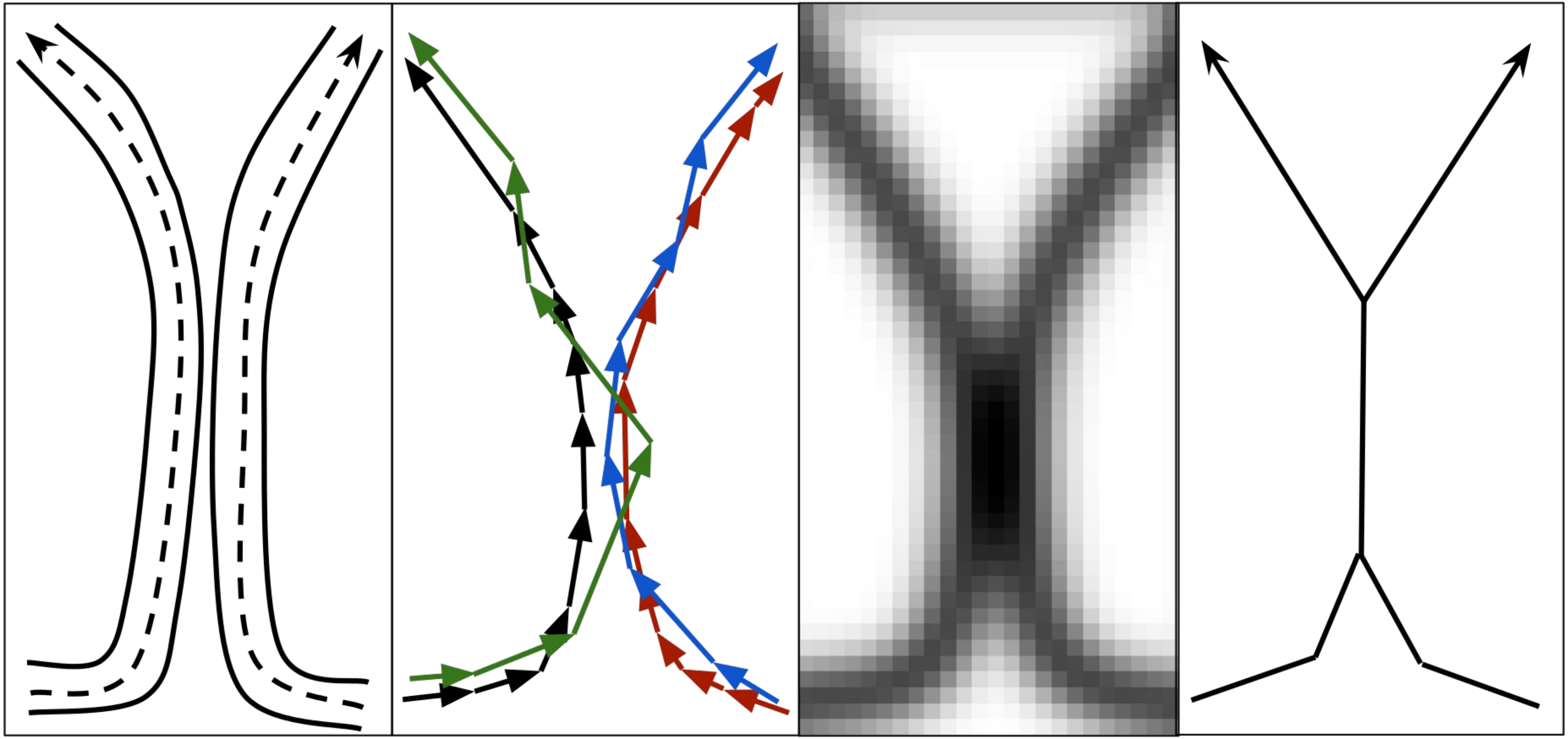
Kernel Density Estimation　　　　　　　　Clustering

Inferring Road Topology: Challenges

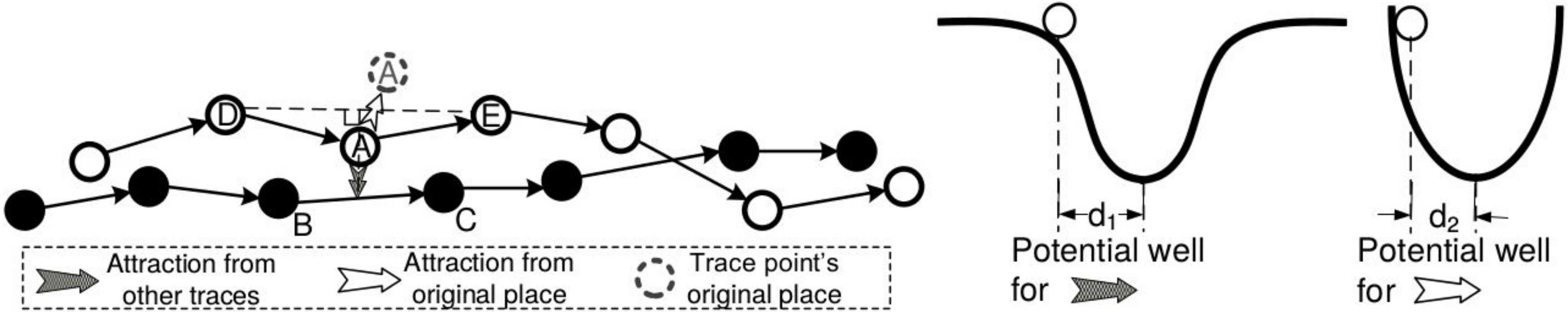
Kernel Density Estimation

Clustering

Inferring Road Topology: Challenges



Inferring Road Topology: Pre-processing Trajectories



(a) Area map (b) GPS data (c) No repelling force (d) With repelling force (e) With improved repelling force

Lili Cao and John Krumm. "From GPS Traces to a Routable Road Map" in ACM SIGSPATIAL (2009).

Inferring Road Topology: Pre-processing Trajectories

- Goal: remove noisy GPS observations
- If the density around a point is less than density around neighbors, then probably the point is noisy
- Compute density in terms of distance to *k*-th nearest neighbor

Zhangqing Shan et al. “COBWEB: A Robust Map Update System Using GPS Trajectories” in UBICOMP (2015).

Pruning Spurious Roads

- Road network graphs inferred by these methods often exhibit noise
- Several methods to refine the graphs, prune noisy segments

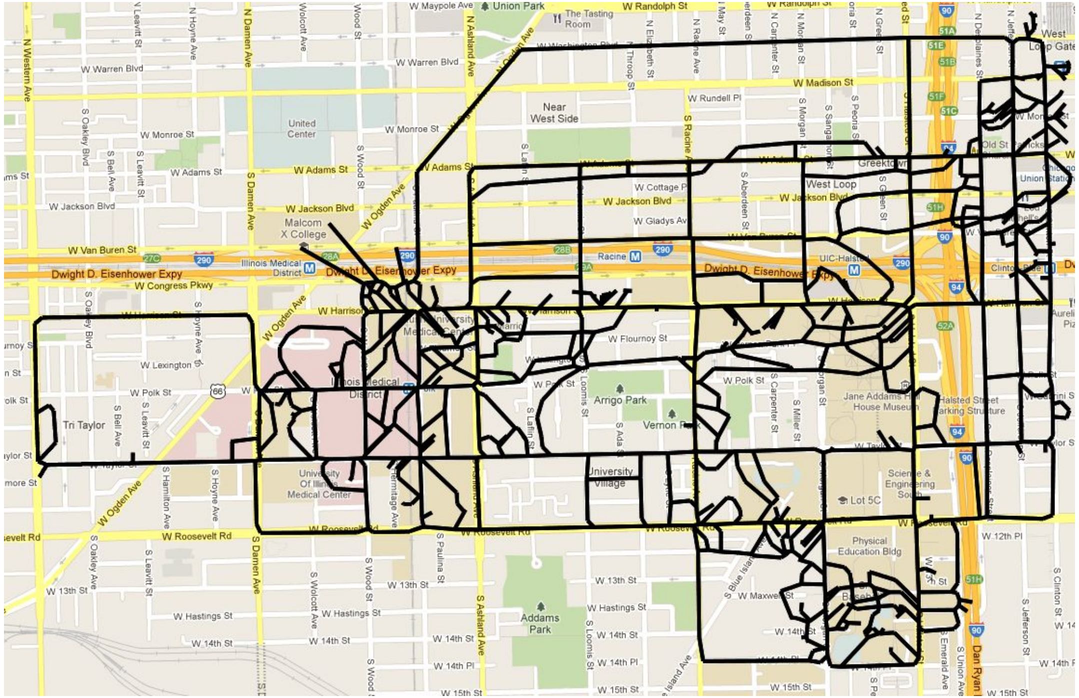
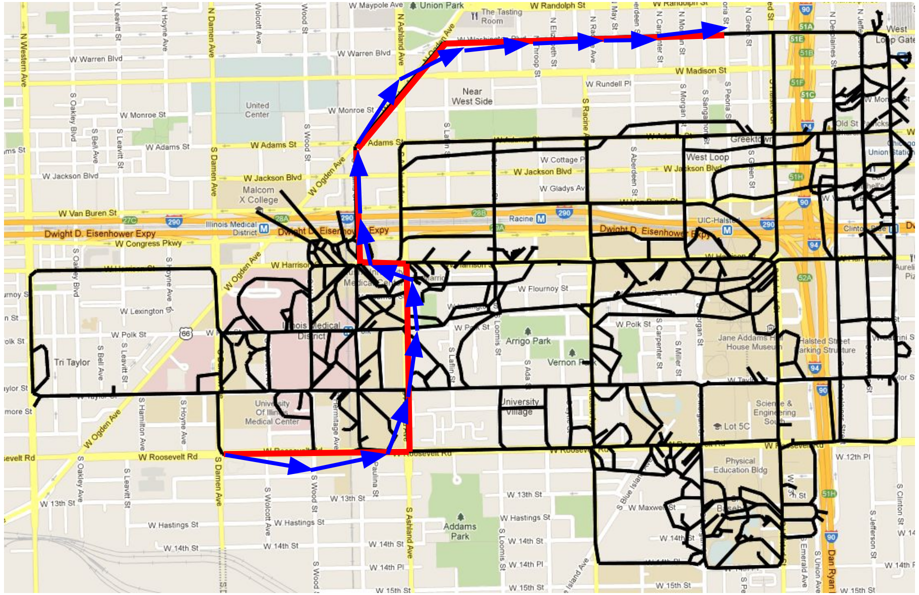


Image from: James Biagioni and Jakob Eriksson. “Map Inference in the Face of Noise and Disparity” in ACM SIGSPATIAL (2012).

Pruning Spurious Roads: Map-Matching

- Map-match trajectories to the initial inferred road network graph
  - For each trajectory, identify a most likely sequence of edges traversed by the vehicle
  - Edges are not equal: each edge is weighted by a confidence score
- Prune edges that are not traversed by enough trajectories



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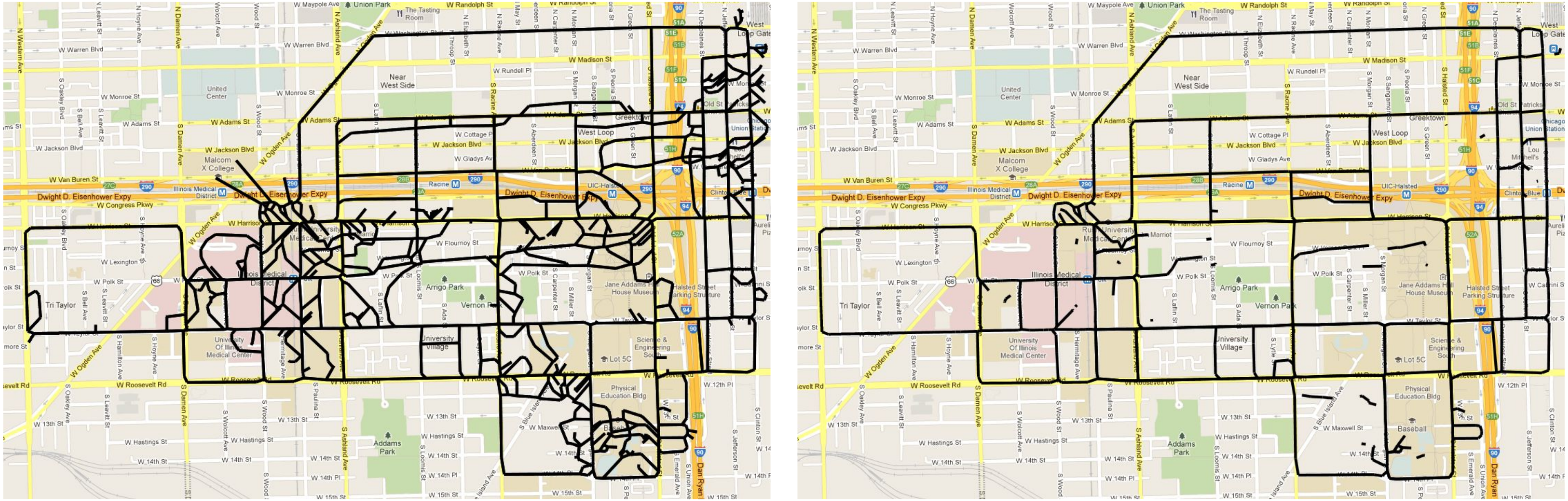

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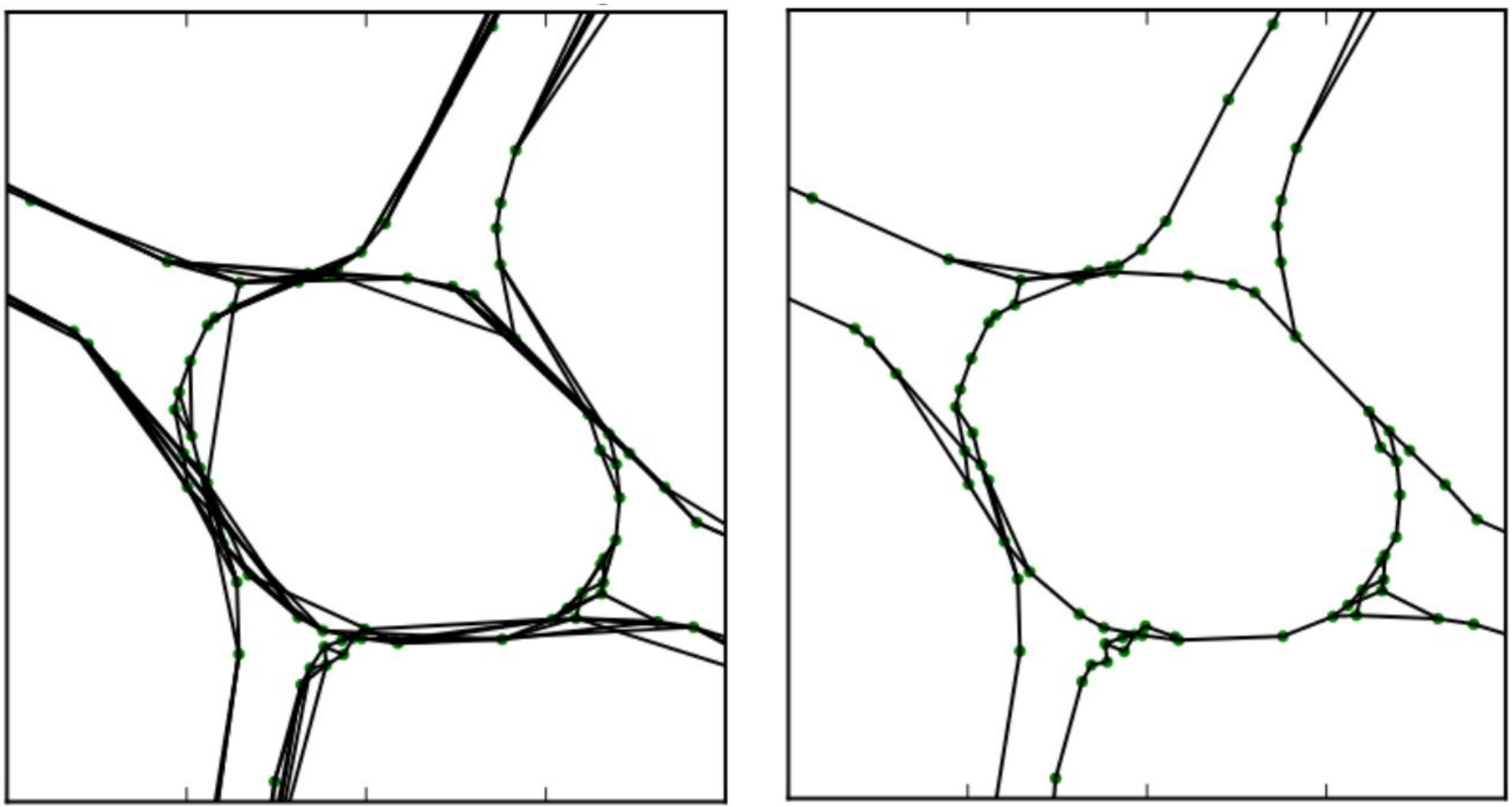
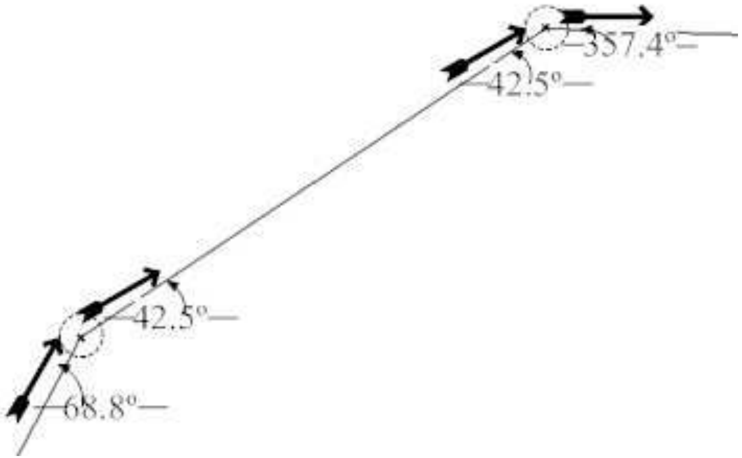
Pruning Spurious Roads: Graph Spanners

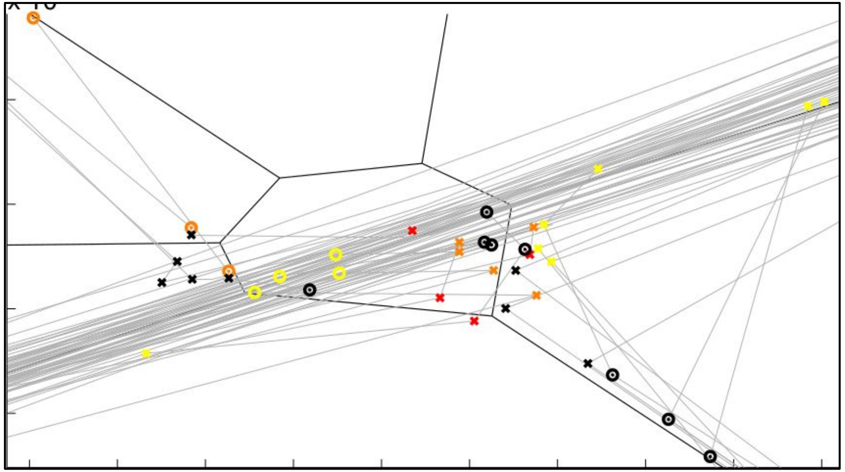


Rade Stanojevic, Sofiane Abbar et al. “Robust Road Map Inference through Network Alignment of Trajectories” in SDM (2018).

Recent Approaches: Intersections First

- Each trajectory: identify turns (vehicle reduces speed and changes heading)
- Cluster nearby turns to identify intersection nodes
- Connect two intersections if a trajectory passes one after the other





Sophia Karagiorgou and Dieter Pfoser. “On Vehicle Tracking Data-Based Road Network Generation” in SIGSPATIAL (2012).

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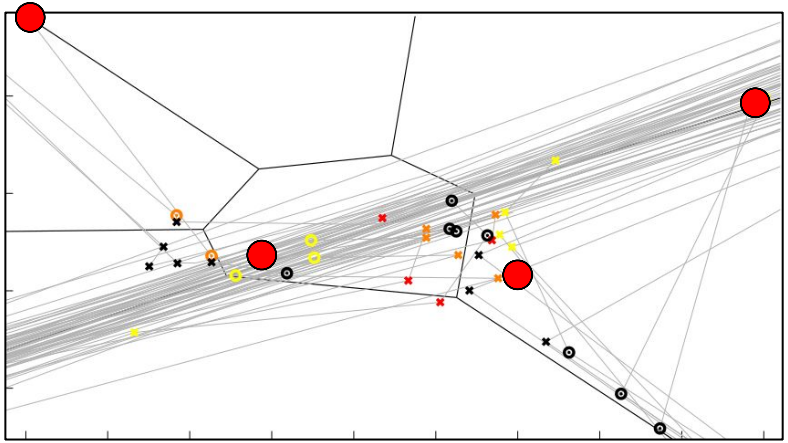

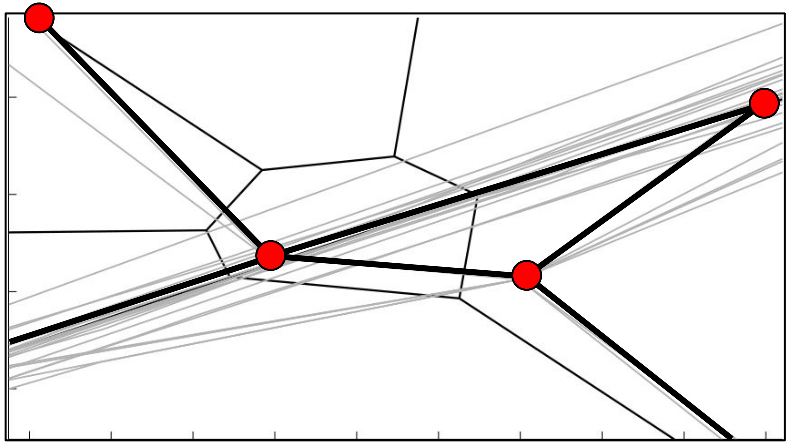

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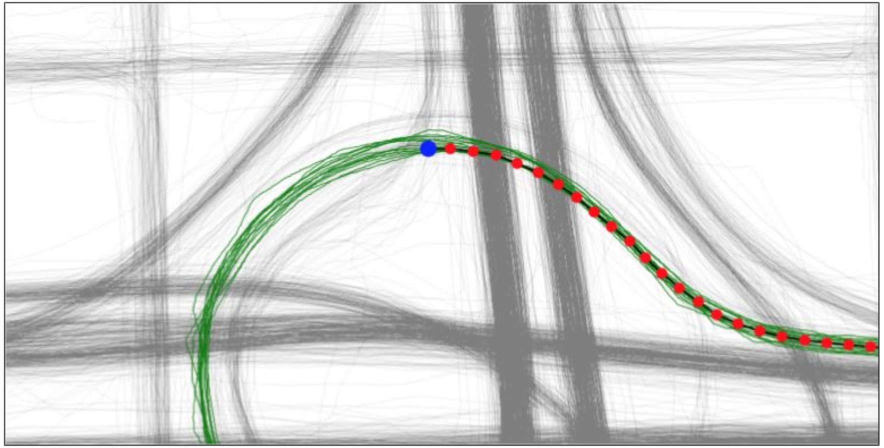
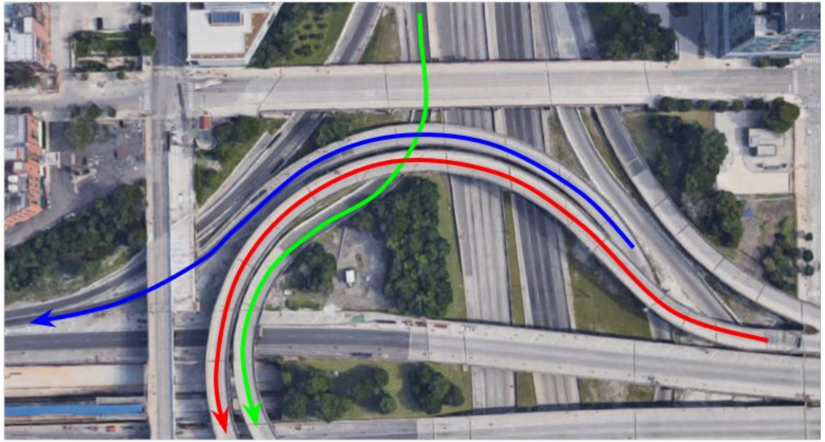
Recent Approaches: Precision First

- Generate a high-precision map first, then improve recall later
- For high precision, use connectivity between observations in the same trajectory





Songtao He, Favyen Bastani et al. “RoadRunner: Improving the Precision of Road Network Inference from GPS Trajectories”.

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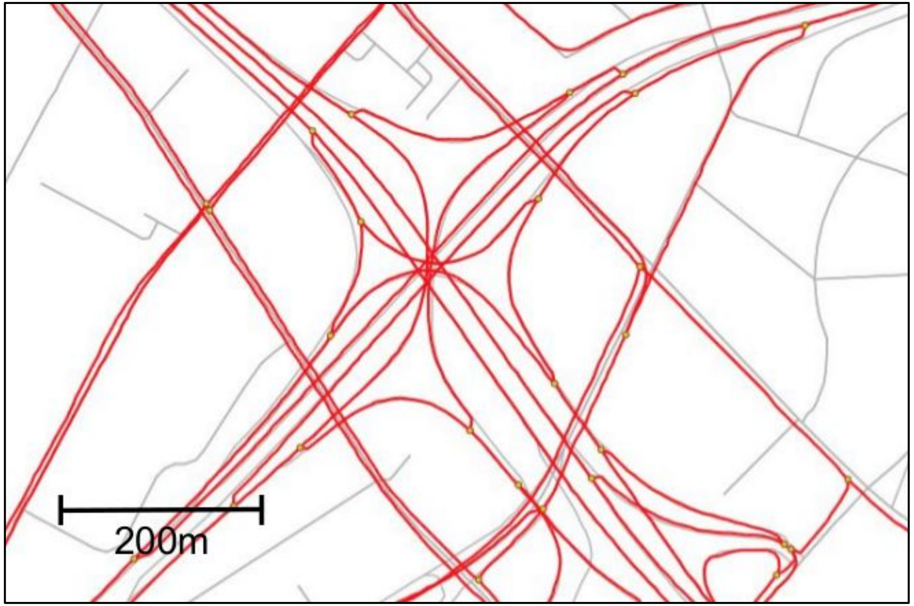
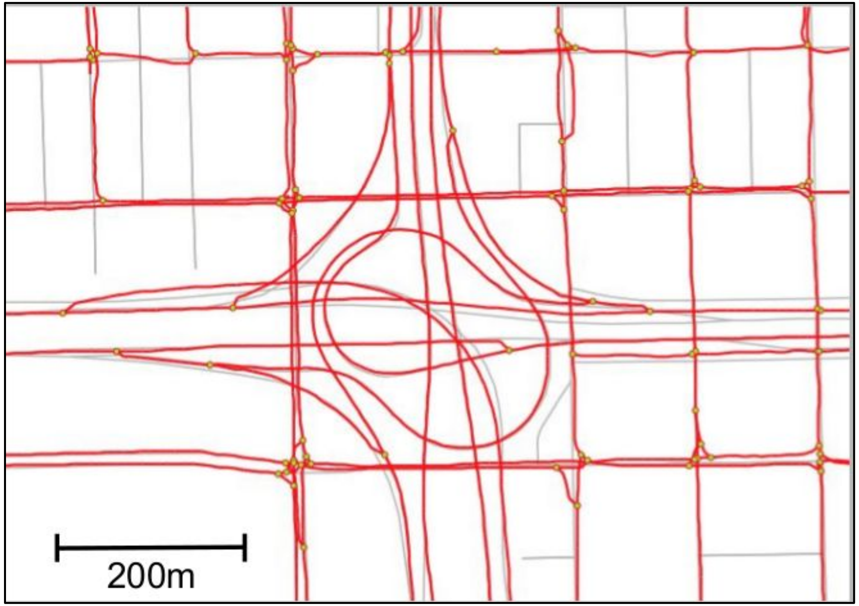




Songtao He, Favyen Bastani et al. “RoadRunner: Improving the Precision of Road Network Inference from GPS Trajectories”.

Integrating Inferred Roads: Map Matching

Input GPS traces

Extracting unmatched segments (red) after map matching

Extracting clusters with sufficient unmatched segments

Fitting new roads (red) to clusters

Yin Wang, Xuemei Liu et al. “CrowdAtlas: Self-Updating Maps for Cloud and Personal Use” in MobiSys (2013).

Integrating Inferred Roads: Map Merging

Need figure showing two maps being merged

Rade Stanojevic, Sofiane Abbar et al. “Road Network Fusion for Incremental Map Updates” in LBS (2018).

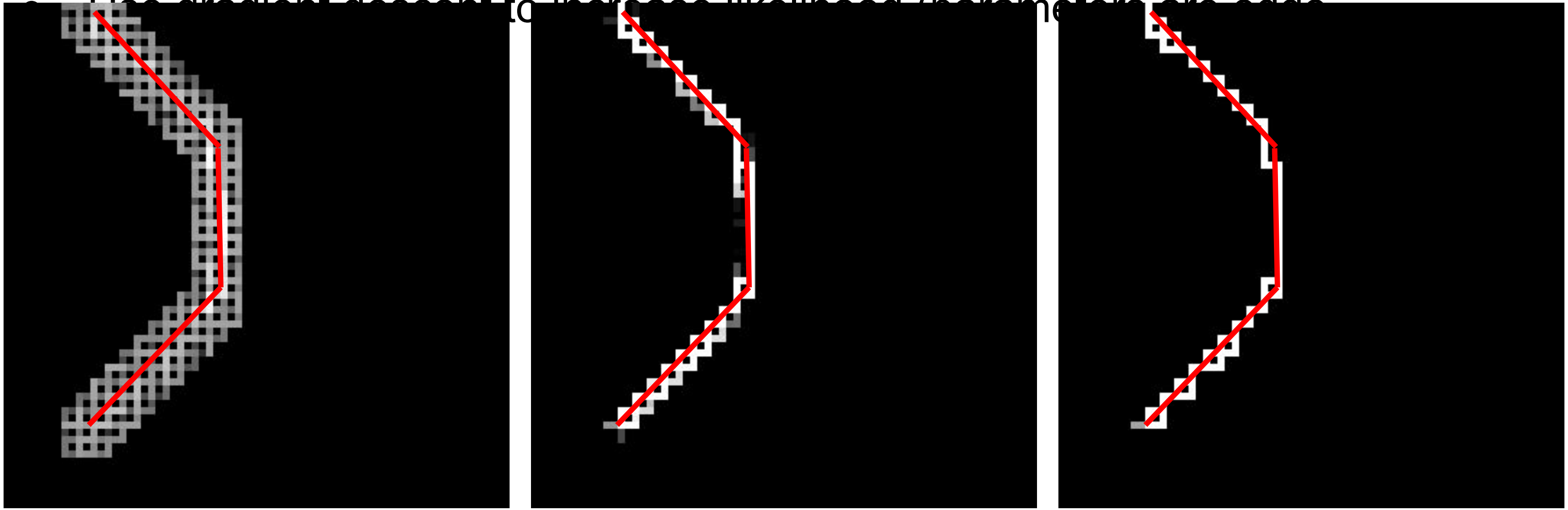
Inferring Road Topology: Potential Future Directions

- Leverage the trajectory connectivity more effectively
- Replace heuristics with better models of GPS noise and vehicle movement
- Supervised learning

Inferring Road Topology: Potential Future Directions

One approach to leverage connectivity, replace heuristics:

- Define likelihood of GPS trajectories given road network (like in map-matching)
- Graph representation: dense grid, with probability associated with each edge
- Goal: output road network graph by zeroing probabilities of undesired edges
- Use gradient descent to increase likelihood (parameters are edge



red: trajectory; white: road network graph (edges weighted by probability)

Inferring Road Topology: Potential Future Directions

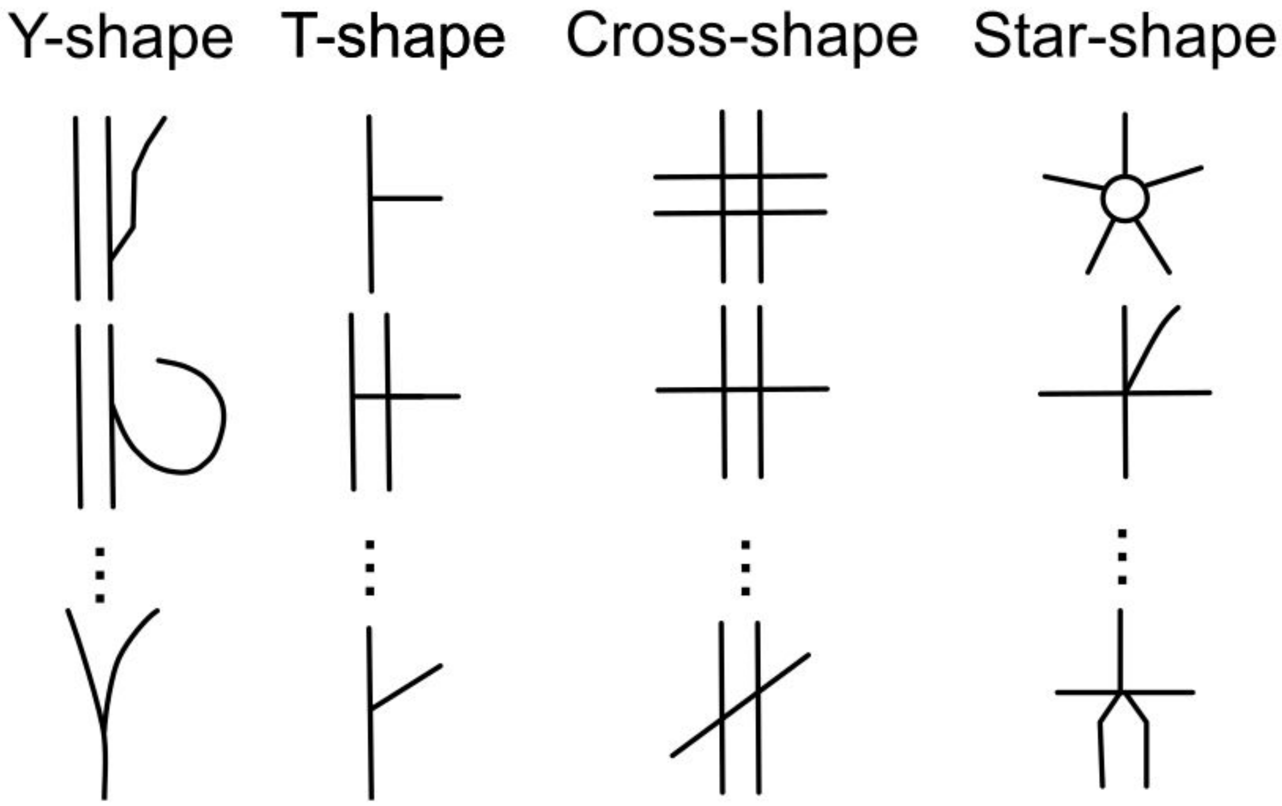
Supervised learning?

- Could enable encoding of priors on what road structures usually look like
- But how to encode GPS trajectories and road network graph for learning?

Some approaches and their drawbacks:

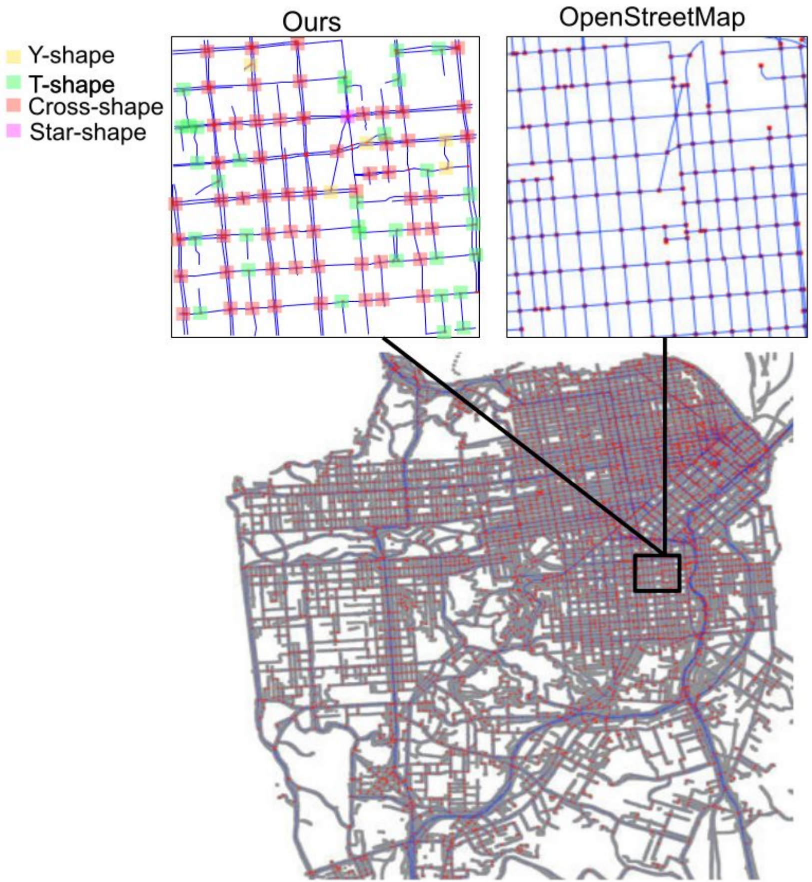
- CNNs: encode trajectories as histogram? But then lose the connectivity
- Graph CNNs: unclear how to encode trajectories, and cannot alter the graph structure (can only move vertices/edges, not add/remove them)

Other Applications: Junction Classification



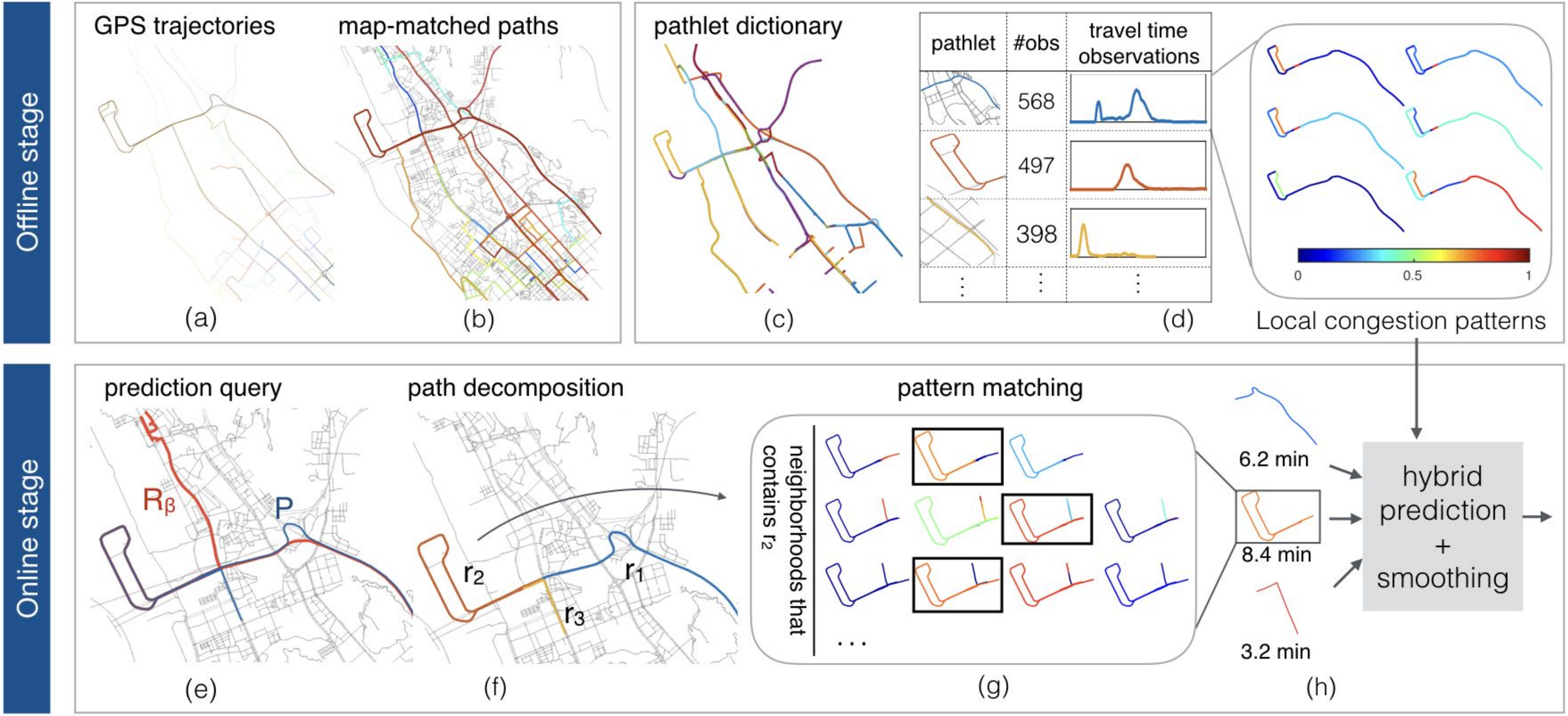
Chen Chen, Cewu Lu et al. “City-Scale Map Creation and Updating using GPS Collections” in KDD (2016).

Other Applications: Junction Classification



Chen Chen, Cewu Lu et al. “City-Scale Map Creation and Updating using GPS Collections” in KDD (2016).

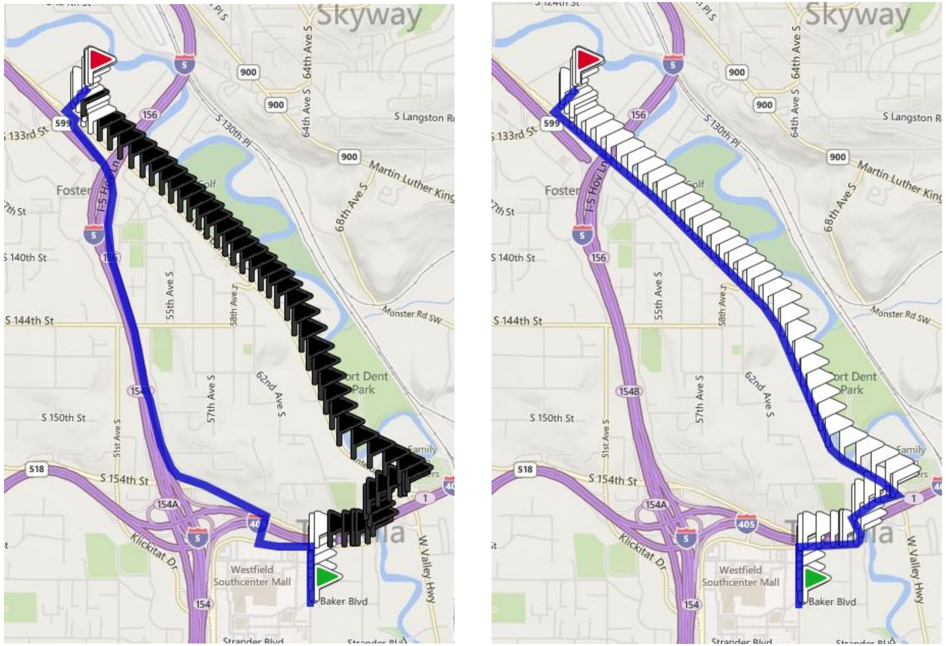
Other Applications: Congestion



Yang Li, Dimitrios Gunopulos et al. “Urban Travel Time Prediction using a Small Number of GPS Floating Cars” in SIGSPATIAL (2017).

Other Applications: Personalized Navigation

- Navigation system accepts various customizable parameters
  - Desirability of different types of turns (e.g. left), roads (e.g. freeway), speeds, etc.
- Automatically learn parameters for each user based on their historical GPS trajectories



Daniel Delling, Andrew Goldberg et al. “Navigation Made Personal: Inferring Driving Preferences from GPS Traces” in SIGSPATIAL (2015).