Mining Moving Object and Traffic Data

DASFAA 2010 Tutorial

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Tutorial Outline

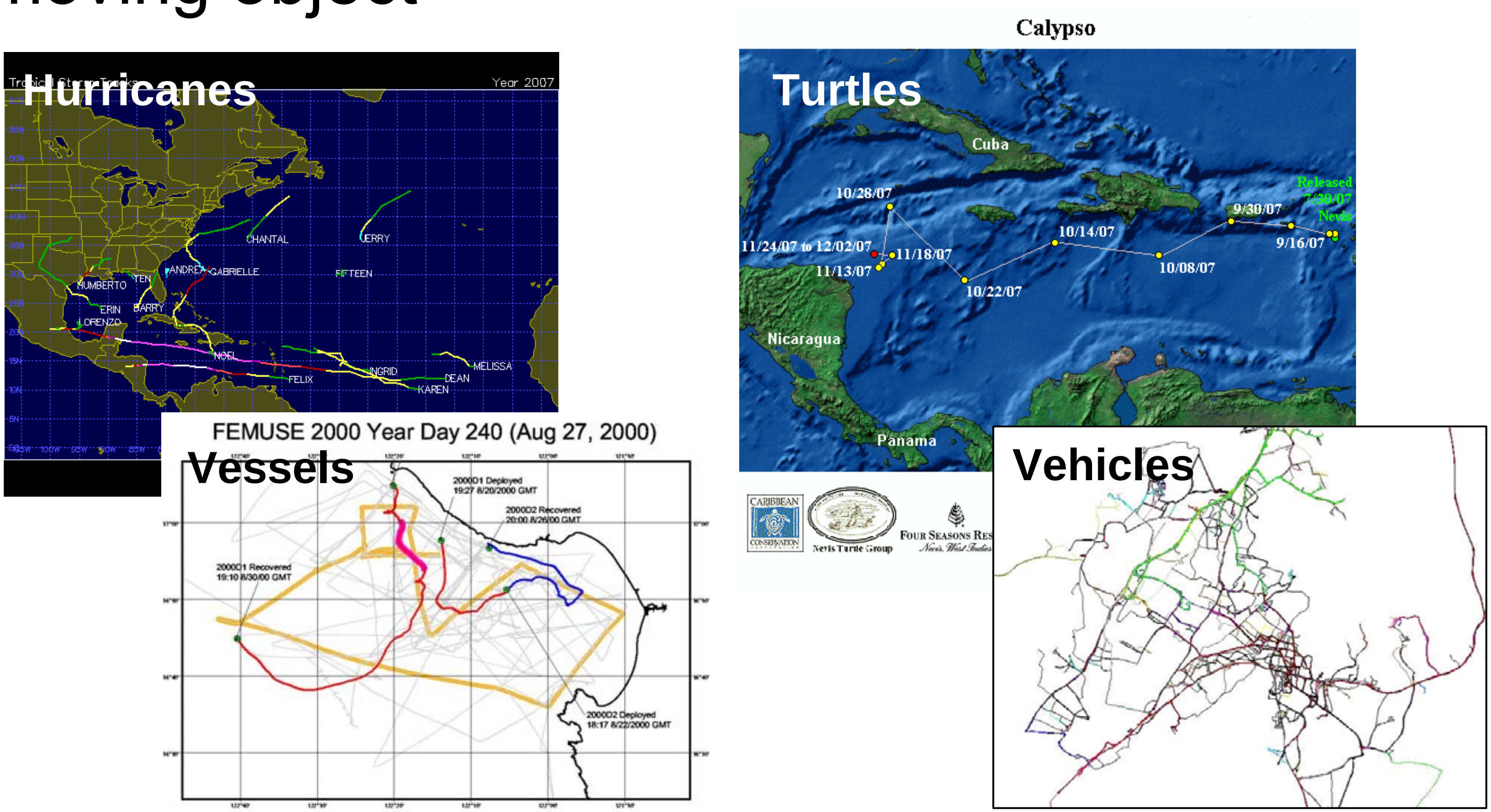
- Part I. Mining Moving Objects
- Part II. Mining Traffic Data
- Part III. Conclusions

Part I. Moving Object Data Mining

- Introduction
- Movement Pattern Mining
- Periodic Pattern Mining
- Clustering
- Prediction
- Classification
- Outlier Detection

Moving Object Data

- A sequence of the location and timestamp of a moving object



Why Mining Moving Object Data?

- Satellite, sensor, RFID, and wireless technologies have been improved rapidly
  - Prevalence of mobile devices, e.g., cell phones, smart phones and PDAs
  - GPS embedded in cars
  - Telemetry attached on animals
- Tremendous amounts of trajectory data of moving objects
  - Sampling rate could be every minute, or even every second
  - Data has been fast accumulated

Complexity of the Moving Object Data

- Uncertainty
  - Sampling rate could be inconstant: From every few seconds transmitting a signal to every few days transmitting one
  - Data be sparse: A recorded location every 3 days
- Noise
  - Erroneous points (e.g., a point in the ocean)
- Background
  - Cars follow underlying road network
  - Animals movements relate to mountains, lakes, ...
- Movement interactions
  - Affected by nearby moving objects

Research Impacts

- Moving object and trajectory data mining has many important, real-world applications driven by the real need
  - Homeland security (*e.g.*, border monitoring)
  - Law enforcement (*e.g.*, video surveillance)
  - Ecological analysis (e.g., animal scientists)
  - Weather forecast
  - Traffic control
  - Location-based service
  - ...

Part I. Moving Object Data Mining

- Introduction
- Movement Pattern Mining
- Periodic Pattern Mining
- Clustering
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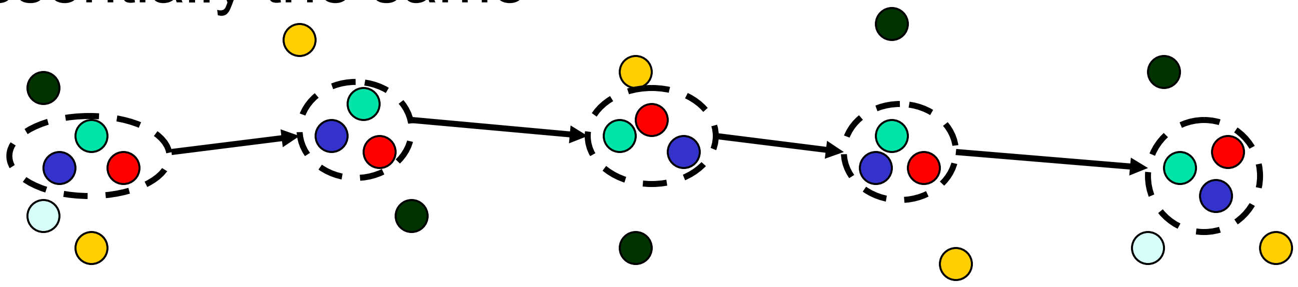
Moving Object Clustering

- A *moving cluster* is a set of objects that move close to each other for a long time interval
  - **Note**: Moving clusters and flock patterns are essentially the same



- Formal Definition [Kalnis et al., SSTD'05]:
  - A *moving cluster* is a sequence of (snapshot) clusters $c_1, c_2, \ldots, c_k$ such that for each timestamp i ($1 \leq i < k$), $|c_i \cap c_{i+1}| / |c_i \cup c_{i+1}| \geq \theta$ ($0 < \theta \leq 1$)

Retrieval of Moving Clusters
(Kalnis et al. SSTD'05)

- Basic algorithm (MC1)
  1. Perform DBSCAN for each time slice
  2. For each pair of a cluster *c* and a moving cluster *g*, check if *g* can be extended by *c*
     - If yes, *g* is used at the next iteration
     - If no, *g* is returned as a result
- Improvements
  - MC2: Avoid redundant checks (Improve Step 2)
  - MC3: Reduce the number of executing DBSCAN (Improve Step 1)

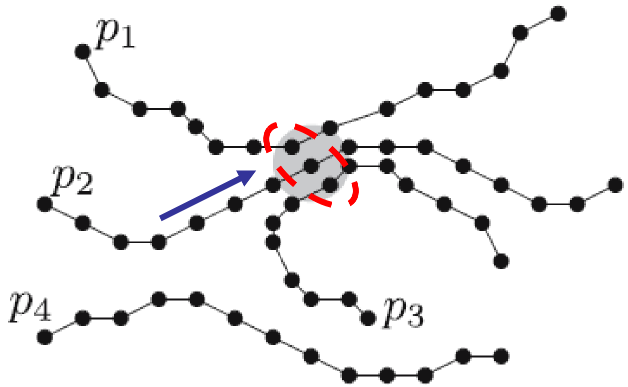
Relative Motion Patterns

(Laube et al. 04, Gudmundsson et al. 07)

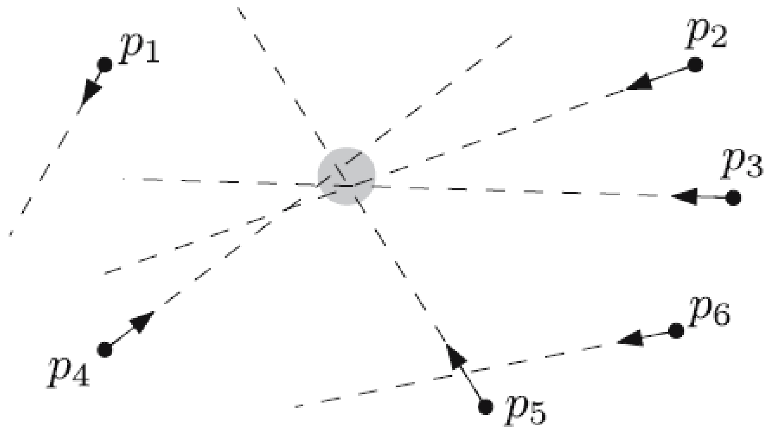
- *Flock* (*m* > 1, *r* > 0): At least *m* entities are within a circular region of **radius *r*** and they move in the same direction
- *Leadership* (*m* > 1, *r* > 0, *s* > 0) At least *m* entities are within a circular region of radius *r*, they move in the same direction, and **at least one of the entities was already heading in this direction for at least *s* time steps**
- *Convergence* (*m* > 1, *r* > 0) At least *m* entities will **pass through** the same circular region of radius *r* (assuming they keep their direction)
- *Encounter* (*m* > 1, *r* > 0) At least *m* entities will be **simultaneously inside** the same circular region of radius *r* (assuming they keep their speed and direction)

Flock, Leadership & Convergence

- Examples



An example of a ***flock*** pattern for p_1, p_2, and p_3 at 8th time step; also a ***leadership*** pattern with p_2 as the leader



A ***convergence*** pattern if m = 4 for p_2, p_3, p_4, and p_5

Complexity of Moving Relationship Pattern Mining

- Algorithms: Exact and approximate algorithms are developed

t is multiplicative factor in all time bounds

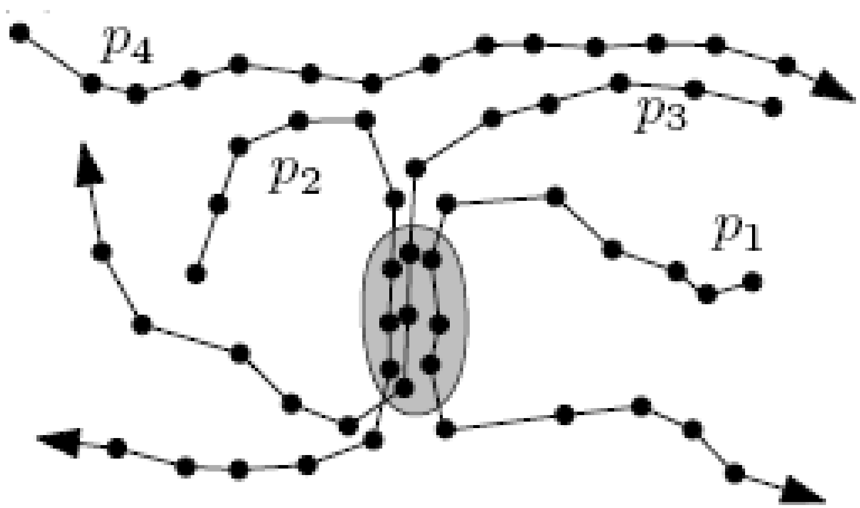
Pattern	Exact (from [15])	Exact (new)	Approximate
Flock	$O(nm^2 + n\log n)$	–	$O(\frac{n}{\varepsilon^2}\log\frac{1}{\varepsilon} + n\log n)$ (radius)
Leadership	$O(ns + nm^2 + n\log n)$	–	$O(ns + \frac{1}{\varepsilon^2}n\log\frac{1}{\varepsilon} + n\log n)$ (radius)
Convergence	$O(n^2)$	–	$O(n^{2+\delta}/(\varepsilon m))$ (subset) $O(\frac{1}{\varepsilon}n^2\log n)$ (radius)
Encounter	$O(n^4)$	$O(n^3)$ (all) $O((m+\log n)n^2)$ (detect) $O((M+\log n)n^2\log M)$ (largest)	

- Flock: Use the higher-order Voronoi diagram
- Leadership: Check the leader condition additionally
- …

An Extension of Flock Patterns

(Gudmundsson et al. GIS'06, Benkert et al. SAC'07)

- A new definition considers *multiple* time steps, whereas the previous definition *only one* time step
- ***Flock***: A *flock* in a time interval *I*, where the duration of *I* is at least *k*, consists of at least *m* entities such that for every point in time within *I*, there is a disk of radius *r* that contains all the *m* entities
  - e.g.,

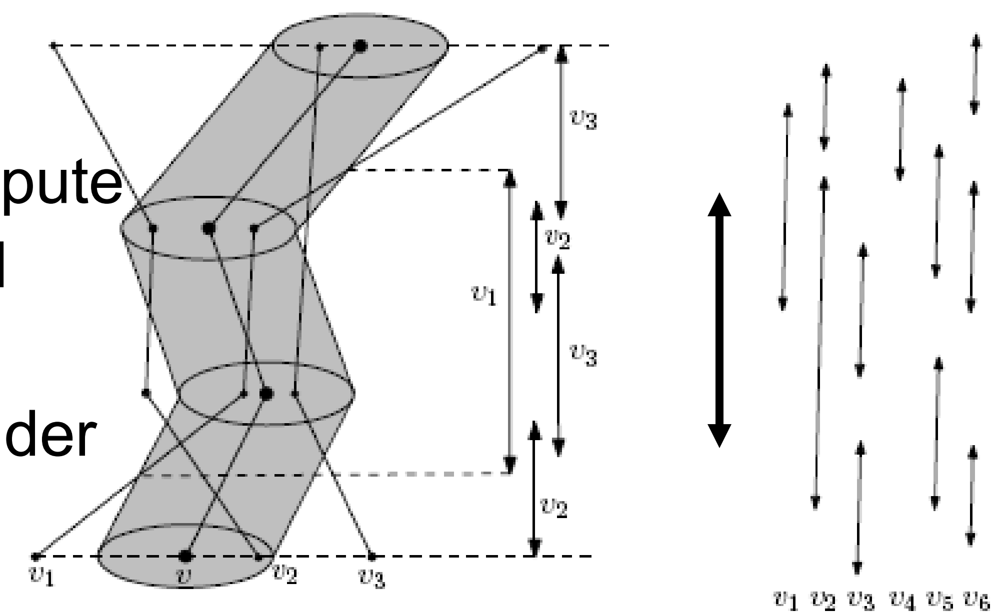


A flock through 3 time steps

Computing Flock Patterns

- *Approximate* flocks
  - Convert overlapping segments of length *k* to points in a *2k*-dimensional space
  - Find *2k*-d pipes that contain at least *m* points

- *Longest duration* flocks
  - For every entity *v*, compute a cylindrical region and the intervals from the intersection of the cylinder
  - Pick the longest one



Convoy: An Extension of Flock Pattern

(Jeung et al. ICDE'08 & VLDB'08)

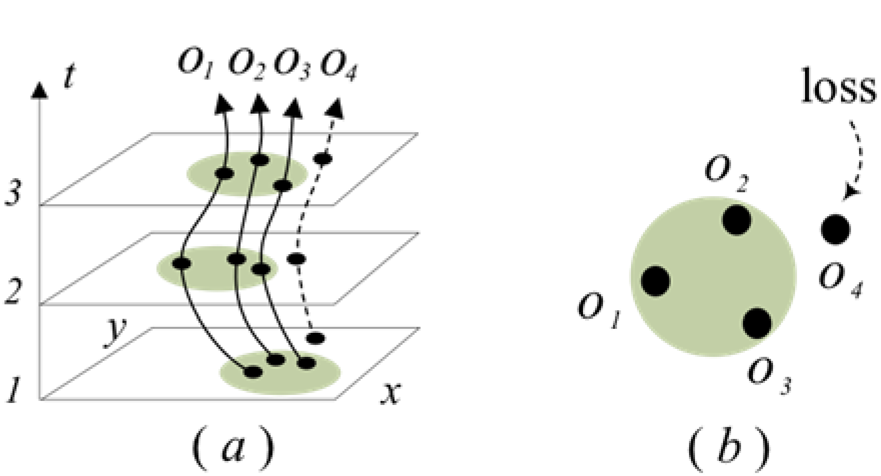


Figure 1: ***Lossy-flock*** **Problem**

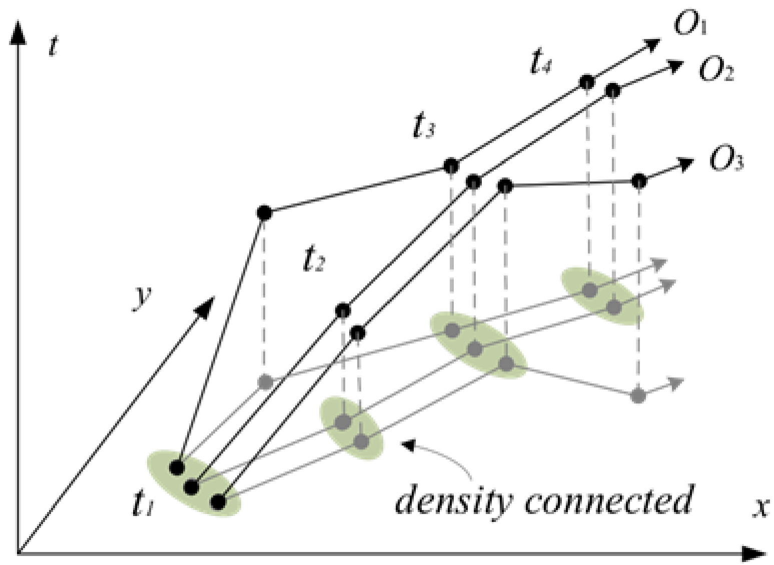


Figure 4: An Example of a Convoy

- Flock pattern has rigid definition with a circle
- Convoy use *density-based clustering* at each timestamp

Efficient Discovery of Convoys

- Base-line algorithm:
  - Calculate density-based clusters for each timestamp
  - Overlap clusters for every k consecutive timestamps
- Speedup algorithm using trajectory simplification
  - Trajectory simplification

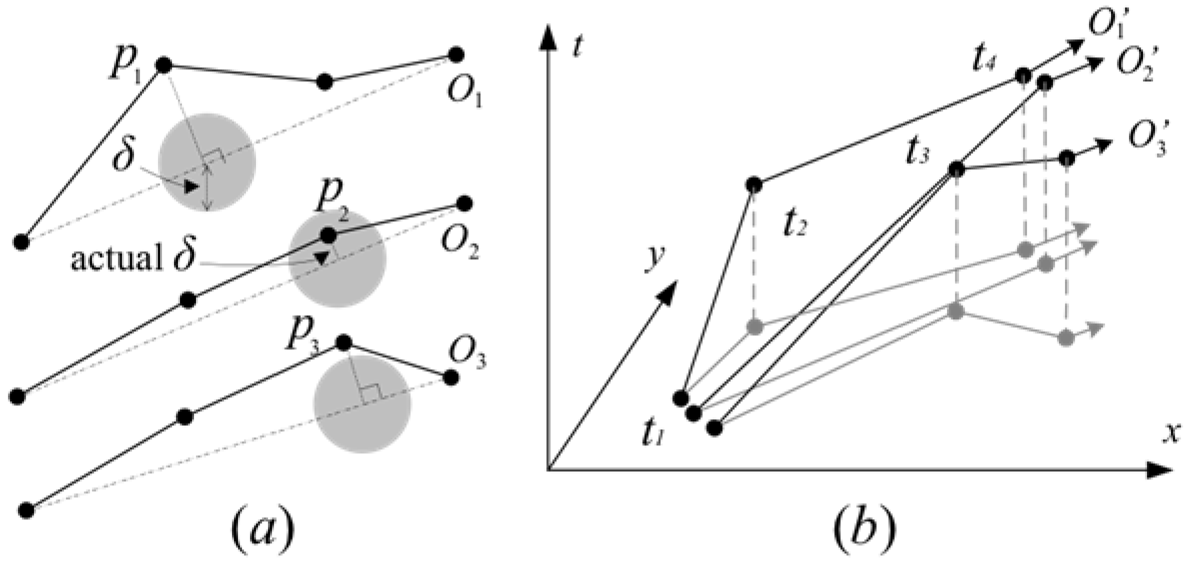


Figure 6: Trajectory Simplification

A Filter-and-Refine Framework for Convoy Mining

- Filter-and-refine framework
  - Filter: partition time into λ-size time slot; a trajectory is transformed into a set of segments; density-based clustering on segments.
  - Refine: Look into every λ-size time slot, refine the clusters based on points.

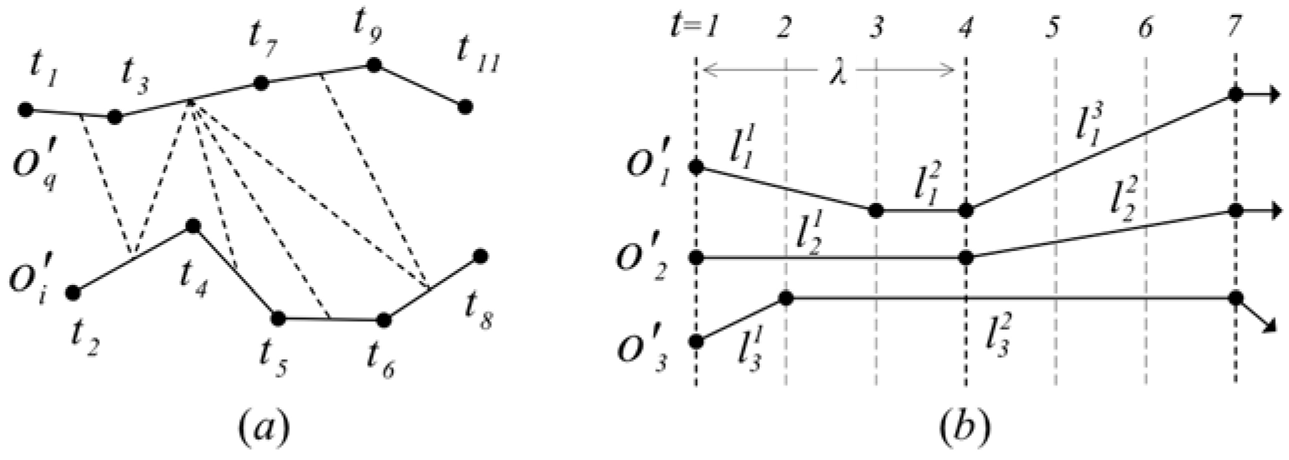
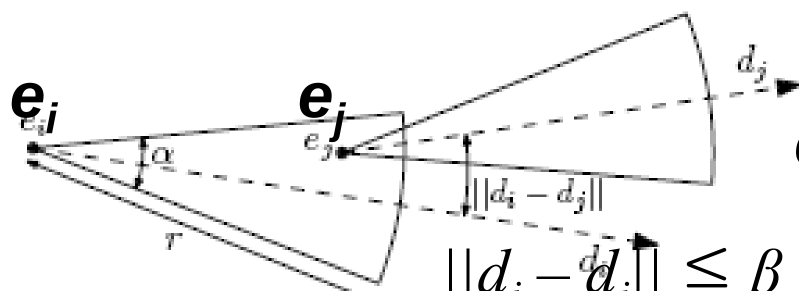


Figure 9: Measure of $\omega(o'_q, o'_i)$ and Time Partitioning

An Extension of Leadership Patterns

(Andersson et al. *GeoInformatica* 07)

- ***Leadership***: if there is an entity that is a leader of at least *m* entities for <u>at least *k* time units</u>
  - An entity e_j is said to be a *leader* at time $[t_x, t_y]$ for time-points t_x, t_y, if and only if e_j does not follow anyone at time $[t_x, t_y]$, and e_j is followed by sufficiently many entities at time $[t_x, t_y]$

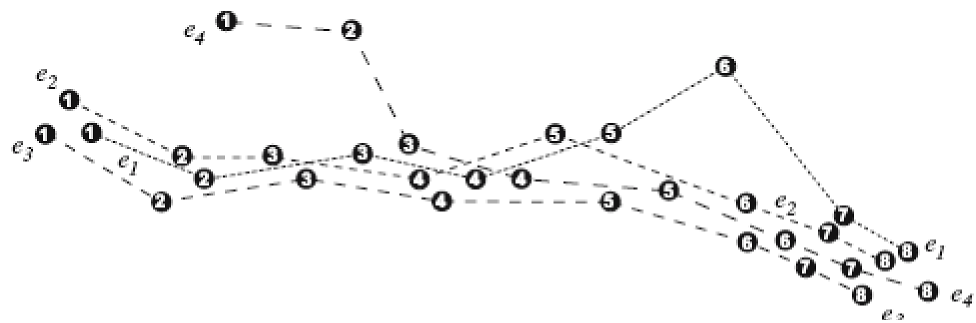


e_i follows e_j

$$||d_i - d_j|| \leq \beta$$

Reporting Leadership Patterns

- Algorithm: Build and use the follow-arrays

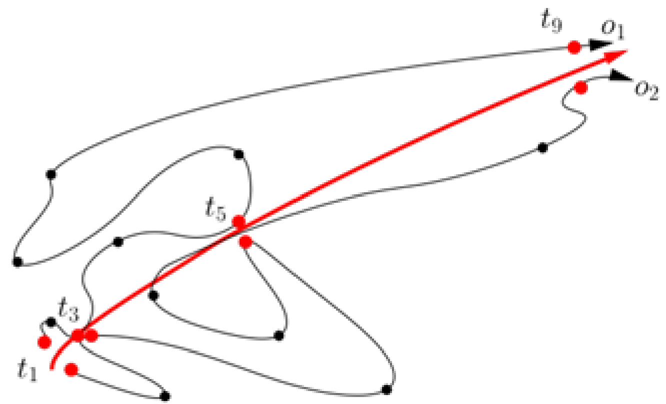


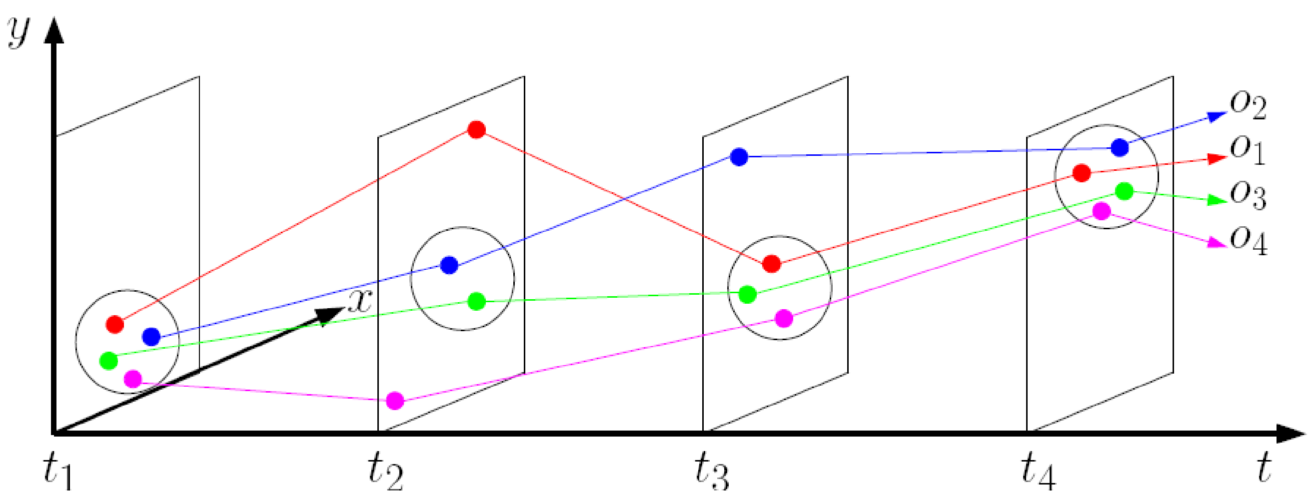
Array	Entity	1	2	3	4	5	6	7	8
IntervalsNotFwg(t):	e_1	0	1	2	0	1	2	3	0
	e_2	0	0	0	0	0	1	0	0
	e_3	0	0	0	0	0	0	0	0
	e_4	0	1	2	3	4	5	6	7
IntervalsFwg(e',t): e_1	e_2	0	1	2	3	4	0	0	0
	e_3	0	1	2	3	0	0	0	0
	e_4	0	0	0	0	0	0	0	0
IntervalsFwg(e',t): e_2	e_1	0	0	0	0	0	0	0	0
	e_3	0	0	0	0	0	0	0	0
	e_4	0	0	0	0	0	0	0	0
IntervalsFwg(e',t): e_3	e_1	0	0	0	0	0	0	0	0
	e_2	0	0	0	1	0	0	0	0
	e_4	0	0	0	0	0	0	0	0
IntervalsFwg(e',t): e_4	e_1	0	0	0	1	0	0	0	1
	e_2	0	0	0	0	0	0	1	2
	e_3	0	0	0	0	1	2	3	4
IntervalsFwd$_m$(t): *(m=1)*	e_1	0	1	2	3	4	0	0	0
	e_2	0	0	0	0	0	0	0	0
	e_3	0	0	0	1	0	0	0	0
	e_4	0	0	0	1	2	3	4	5
numFws(t):	e_1	0	2	2	2	1	0	0	0
	e_2	0	0	0	0	0	0	0	0
	e_3	0	0	0	1	0	0	0	0
	e_4	0	0	0	1	1	1	2	3

e.g., Store nonnegative integers specifying for how many past consecutive unit-time-intervals e_j is following e_i ($e_j \neq e_i$)

Swarms: A Relaxed but Real, Relative Movement Pattern

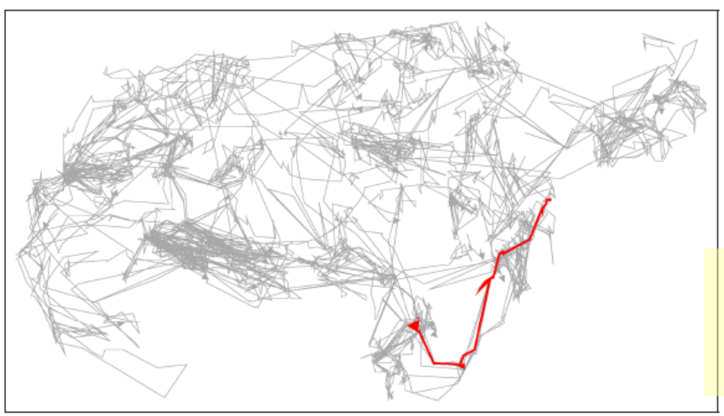
- Flock and convoy all require k consecutive time stamps (still very rigid definition)
- Moving objects may not be close to each other for consecutive time stamps (need to relax time constraint)





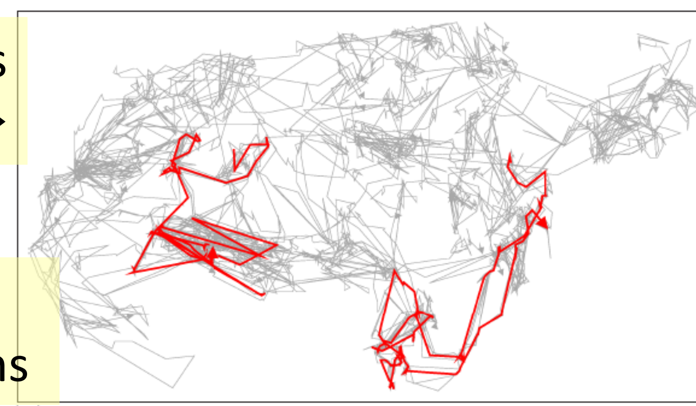
Discovery of Swarm Patterns

- A system that mines moving object patterns: Z. Li, et al., "**MoveMine: Mining Moving Object Databases**", SIGMOD'10 (system demo)
- Z. Li, B. Ding, J. Han, and R. Kays, "**Swarm: Mining Relaxed Temporal Moving Object Clusters**", in submission



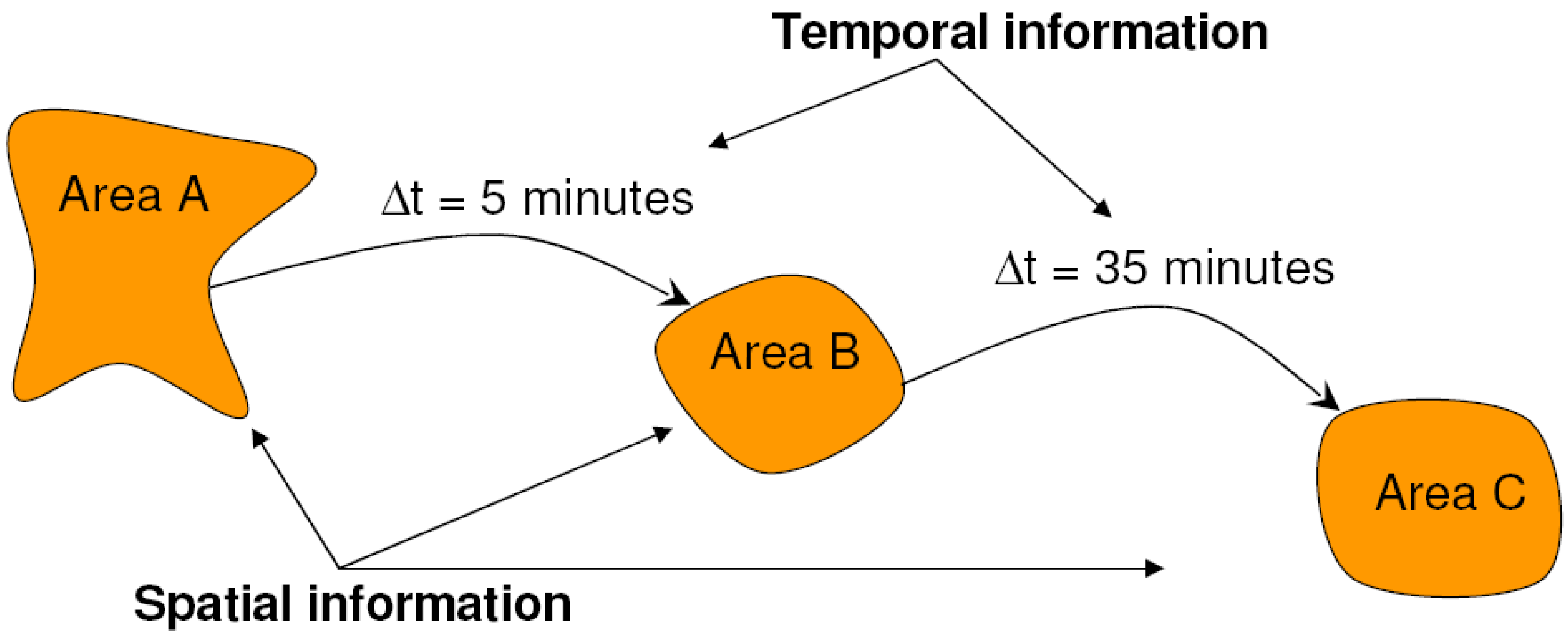
Swarm discovers more patterns →

← **Convoy** discovers only restricted patterns



Trajectory Pattern Mining
(Giannotti et al. KDD 07)

- A trajectory pattern should describe the movements of objects both in space and in time



Trajectory (T-) Patterns: Definition

- A *Trajectory Pattern* (*T-pattern*) is a couple (s, α):
  - s = <(x_0,y_0),..., (x_k,y_k)> is a sequence of k+1 locations
  - α = <α_1,..., α_k> are the transition times (annotations)

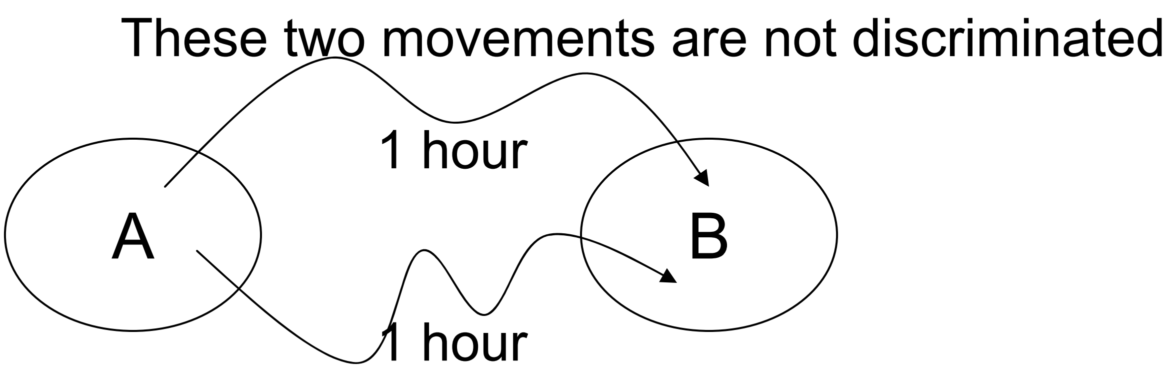
  also written as:

$$(x_0,y_0) \xrightarrow{\alpha_1} (x_1,y_1) \xrightarrow{\alpha_2} \ldots\ldots \xrightarrow{\alpha_k} (x_k,y_k)$$

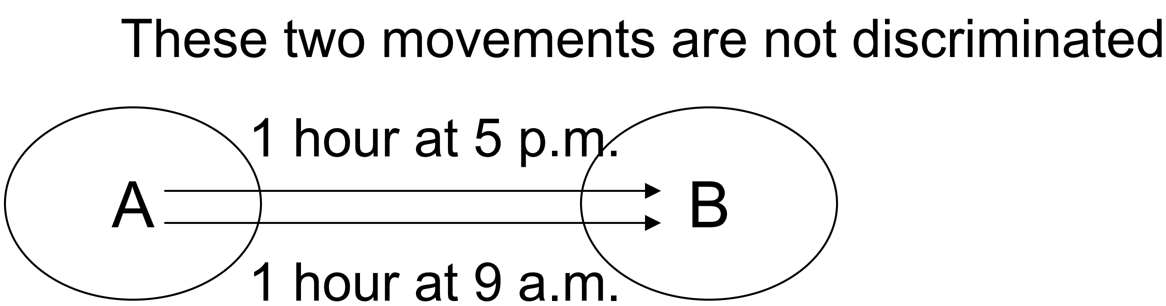
- A T-pattern T_p *occurs* in a trajectory if the trajectory contains a subsequence S such that:
  - Each (x_i,y_i) in T_p matches a point (x_i',y_i') in S, and the transition times in T_p are similar to those in S

Characteristics of Trajectory-Patterns

- Routes between two consecutive regions are not relevant

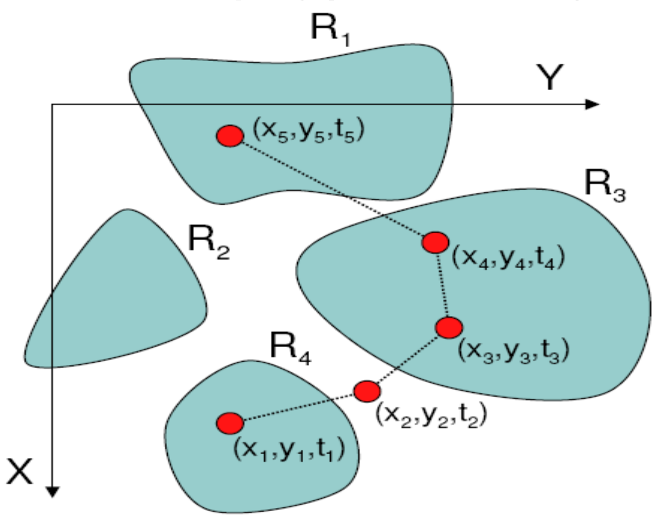


- Absolute times are not relevant



Trajectory-Pattern Mining

- Convert each trajectory to a sequence, *i.e.*, by converting a location (x, y) into a region



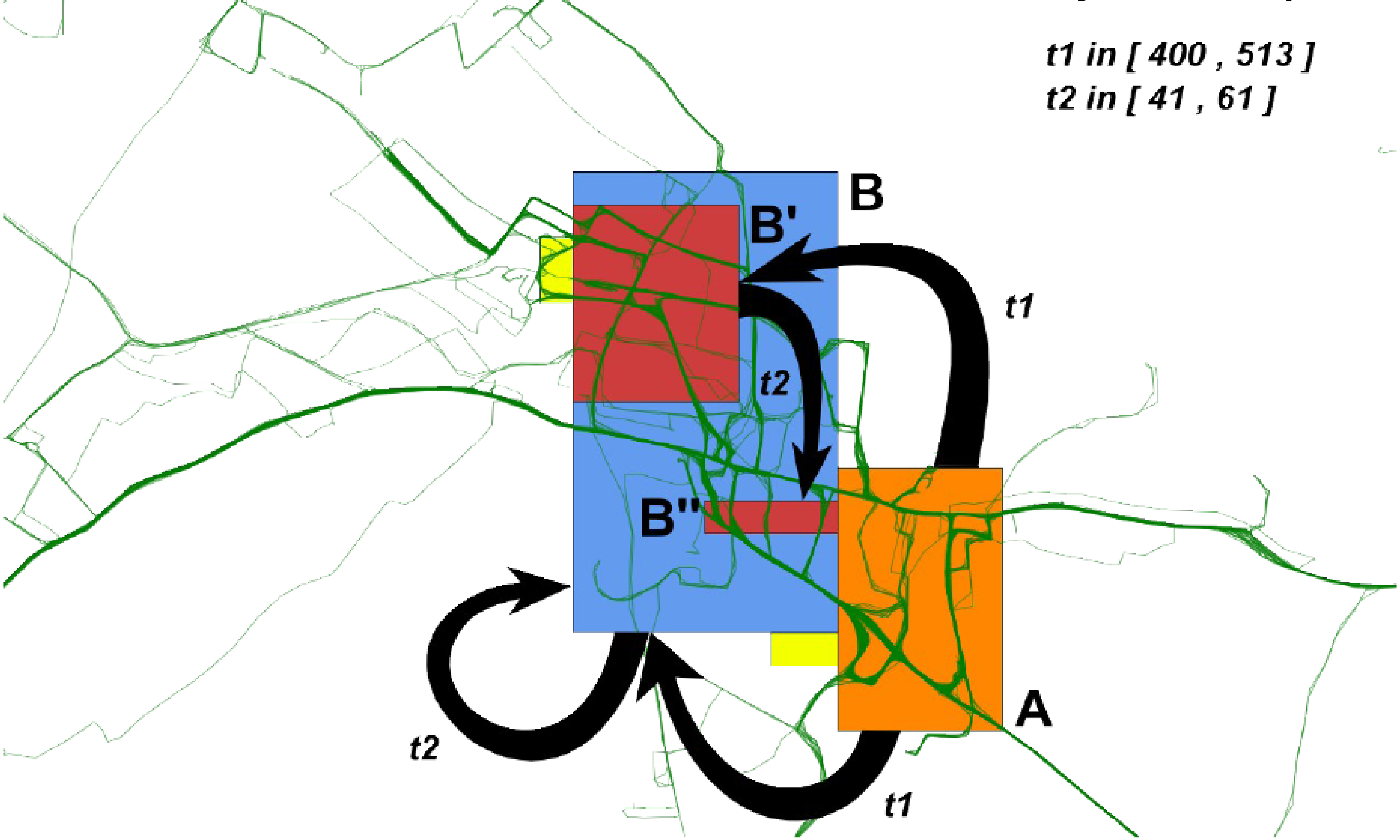
$S=<(x_1,y_1,t_1), \ldots, (x_5,y_5,t_5)>$

$<(R_4,t_1), (R_3,t_3), (R_3,t_4), (R_1,t_5)>$

- Execute the *TAS* (*temporally annotated sequence*) algorithm, over the set of converted trajectories
  - A *TAS* is a sequential pattern annotated with typical transition times between its elements
  - The algorithm of TAS mining is an extension of PrefixSpan so as to accommodate transition times

Sample Trajectory-Patterns

Data Source: Trucks in Athens – 273 trajectories)



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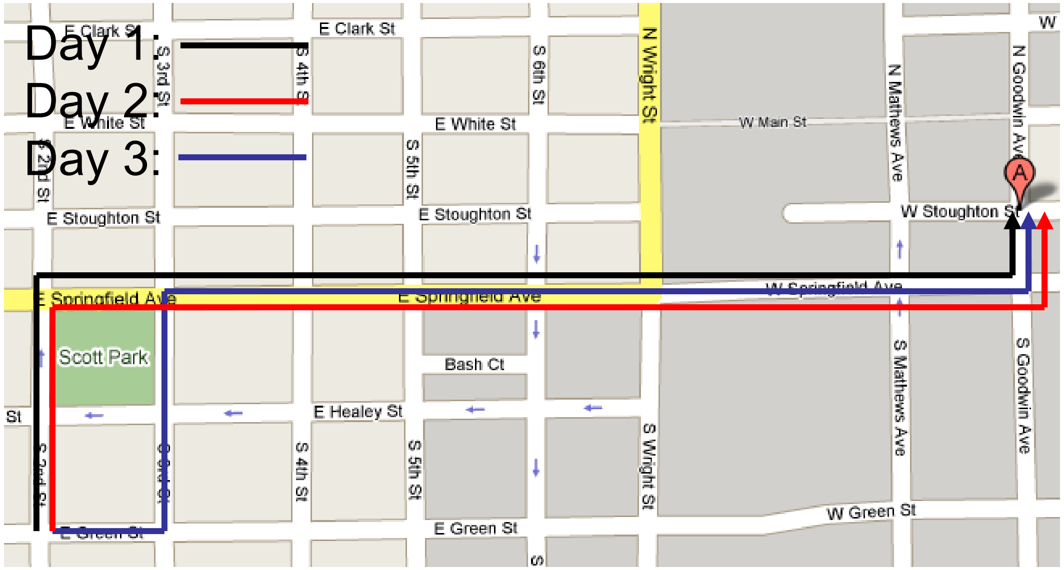
Spatiotemporal Periodic Pattern
(Mamoulis et al. KDD 04)

- In many applications, objects follow the same routes (approximately) over regular time intervals
  - e.g., Bob wakes up at the same time and then follows, more or less, the same route to his work everyday



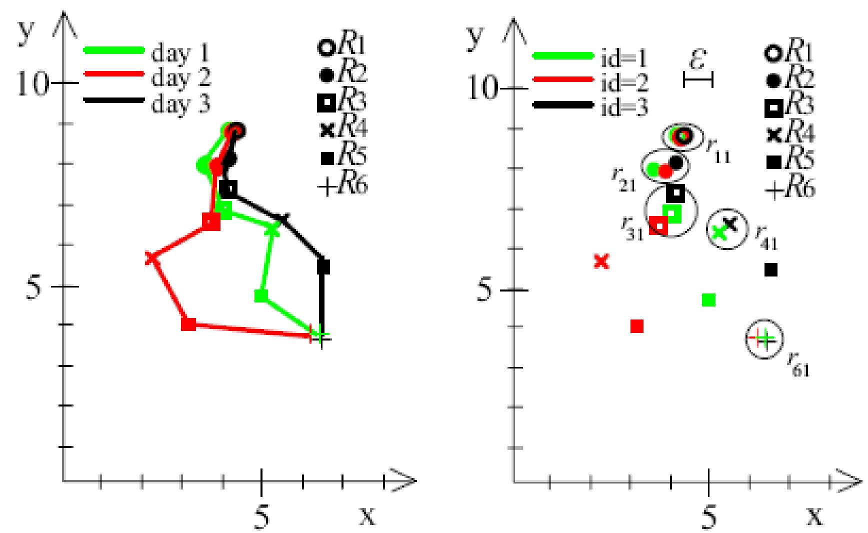
Period and Periodic Pattern

- Let ***S*** be a sequence of *n* spatial locations, $\{l_0, l_1, \ldots, l_{n-1}\}$, representing the movement of an object over a long history
- Let *T* << *n* be an integer called *period, and T is given*
- A *periodic pattern P* is defined by a sequence $r_0 r_1 \ldots r_{T-1}$ of length *T* that appears in ***S*** by more than *min_sup* times
  - For every r_i in *P*, r_i = * or l_{j*T+i} is inside r_i

Periodic Pattern Mining (I)

1. Obtain frequent 1-patterns

- Divide the sequence ***S*** of locations into *T* spatial datasets, one for each offset of the period *T*, *i.e.*, locations $\{l_i, l_{i+T}, \ldots, l_{i+(m-1)T}\}$ go to a set R_i
- Perform DBSCAN on each dataset
  - e.g.,

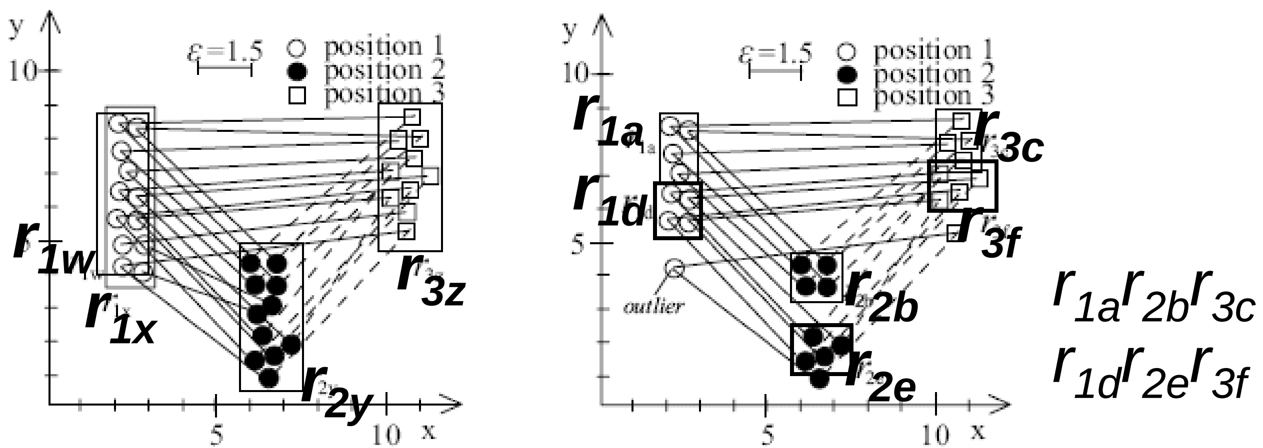


Five clusters discovered in datasets R_1, R_2, R_3, R_4, and R_6

Periodic Pattern Mining (II)

2. Find longer patterns: Two methods

- Bottom-up level-wise technique
  - Generate *k*-patterns using a pair of (*k*-1)-patterns with their first *k*–2 non-* regions in the same position
  - Use a variant of the Apriori-TID algorithm



2-length patterns   generated 3-length patterns

Periodic Pattern Mining (III)

- Faster top-down approach
  - Replace each location in ***S*** with the cluster-id which it belongs to or with * if the location belongs to no cluster
  - Use the sequence mining algorithm to discover fast all frequent patterns of the form $r_0 r_1 \ldots r_{T-1}$, where each r_i is a cluster in a set R_i or *
  - Create a max-subpattern tree and traverse the tree in a top-down, breadth-first order

Periodic Patterns of Moving objects

- Periodic behavior is the intrinsic behavior for most moving objects
  - Yearly migration of birds
    - Fly to south for winter, fly back to north for summer
  - People's daily routines
    - Go to office at 9:00am, back home around 6:00pm
- Detecting periodic behavior is useful for:
  - Summarizing over long historical movement
    - People's behavior could be summarized as some daily behavior and weekly behavior
  - Predicting future movement
    - E.g., predict the location at the *future* time (next day, next week, or next year)
  - Help detect abnormal events
    - A bird does not follow its usual migration path ⇒ a signal of environment change

Challenges of Periodic Pattern Mining

interleaved periods

Raw data of David's movement	Hidden periodic behaviors

…
2009−02−05 07:01 (601, 254)
2009−02−05 09:14 (811, 60)
2009−02−05 10:58 (810, 55)
2009−02−05 14:29 (820, 100)
…
2009−06−12 09:56 (110, 98)
2009−06−12 11:20 (101, 65)
2009−06−12 20:08 (20, 97)
2009−06−12 22:19 (15, 100)
…

- Periodic Behavior #1
  (Period: day; Time span: Sept. − May)
  9:00−18:00 in the office
  20:00−8:00 in the dorm
- Periodic Behavior #2
  (Period: day; Time span: June − Aug.)
  8:00−18:00 in the company
  20:00−7:30 in the apartment
- Periodic Behavior #3
  (Period: week; Time span: Sept. − May)
  13:00−15:00 Mon. and Wed. in the classroom
  14:00−16:00 Tues. and Thurs. in the gym

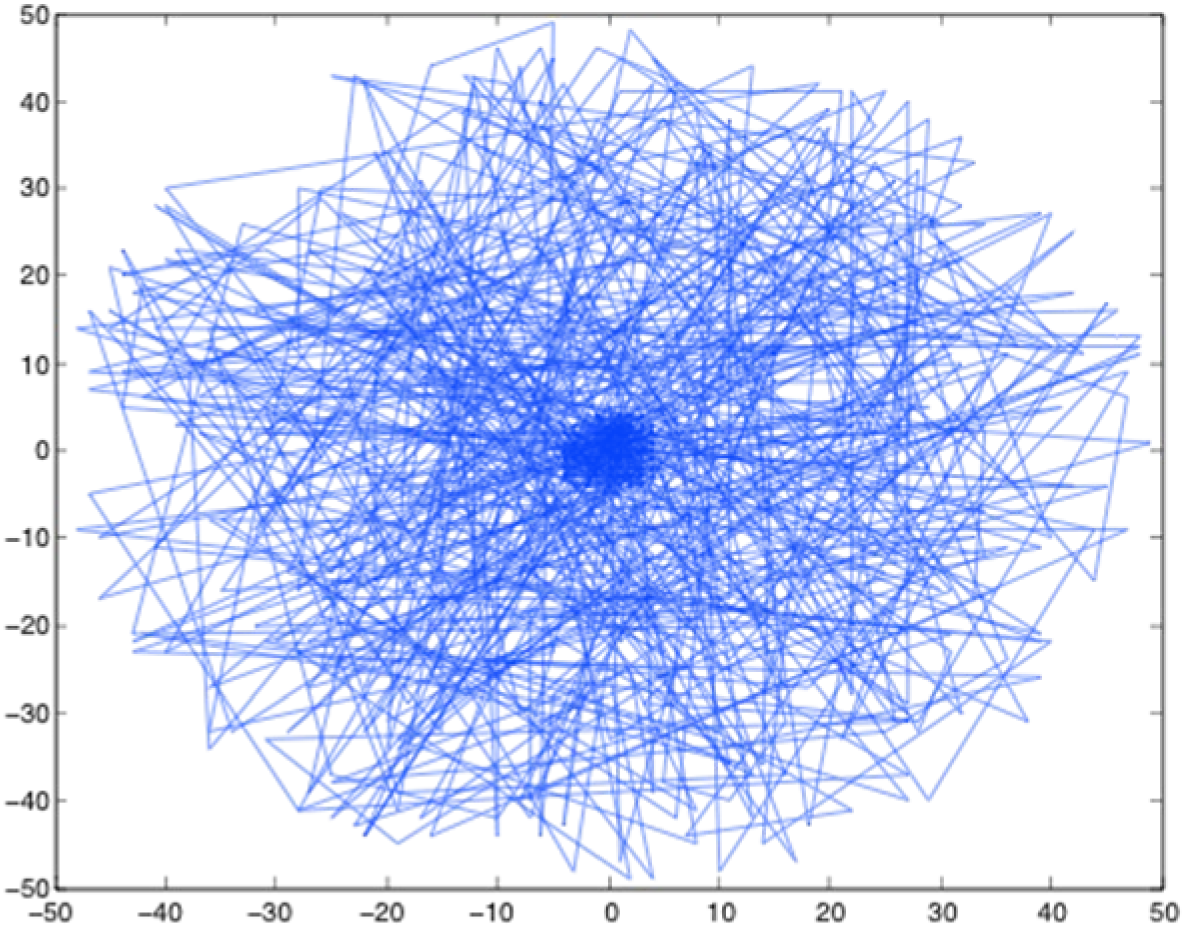
multiple periods

different locations

Detection of Periods: A Naïve Method

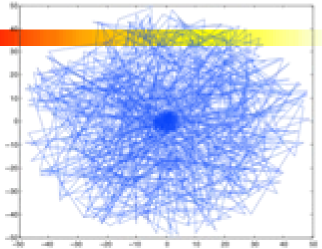
- Transform the movement points into complex plane
  - (x, y) → x-yi
  - (x, y) → y-xi
- Apply Fourier Transform
- Weakness:
  - Affected by noise
  - (x, y) → x-yi and y-xi, each produce different result
  - It cannot detect partial period
    - Short FFT solves partial period problem, but it is not easy to generalize the result

A Motivating Example: Trajectories of Bees



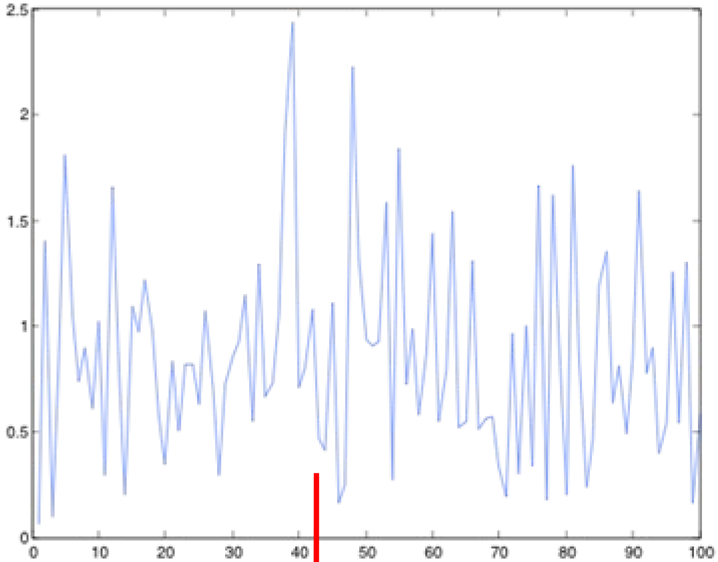
Bee and Flower:
8 hours stays in the nest
16 hours fly nearby

FFT Transformation Does Not Work

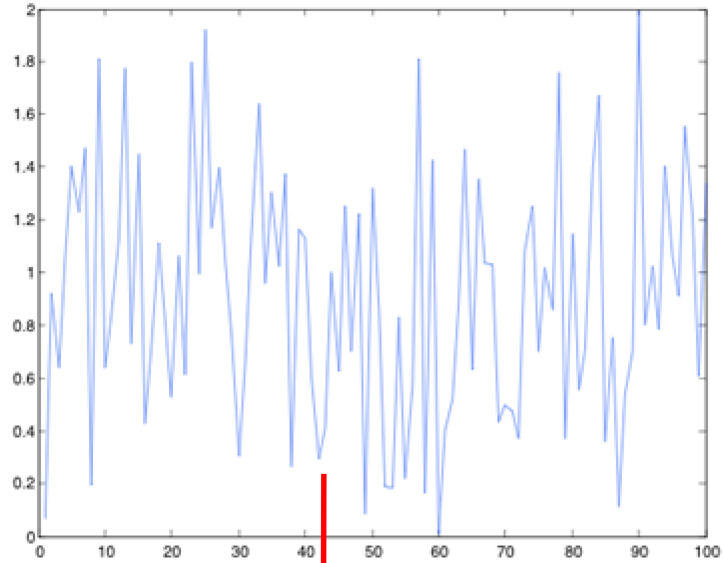


Transform (x,y) into complex plane (two ways to transform)

(x,y) => x-yi

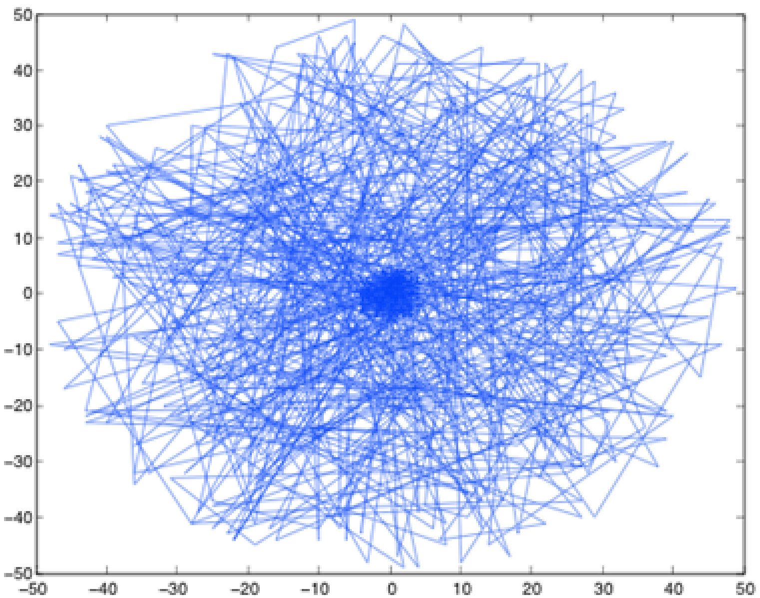


(x,y) => y-xi



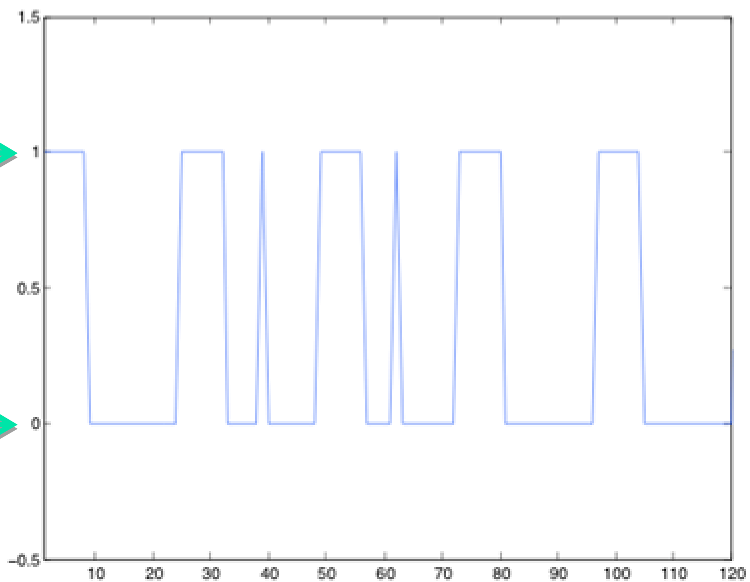
FFT should have strongest power at **42.7** (T = 24, NFFT/T = 1024/24 = 42.7)
Failed!

Observation/Reference Spot: The Nest



in the nest

not in the nest



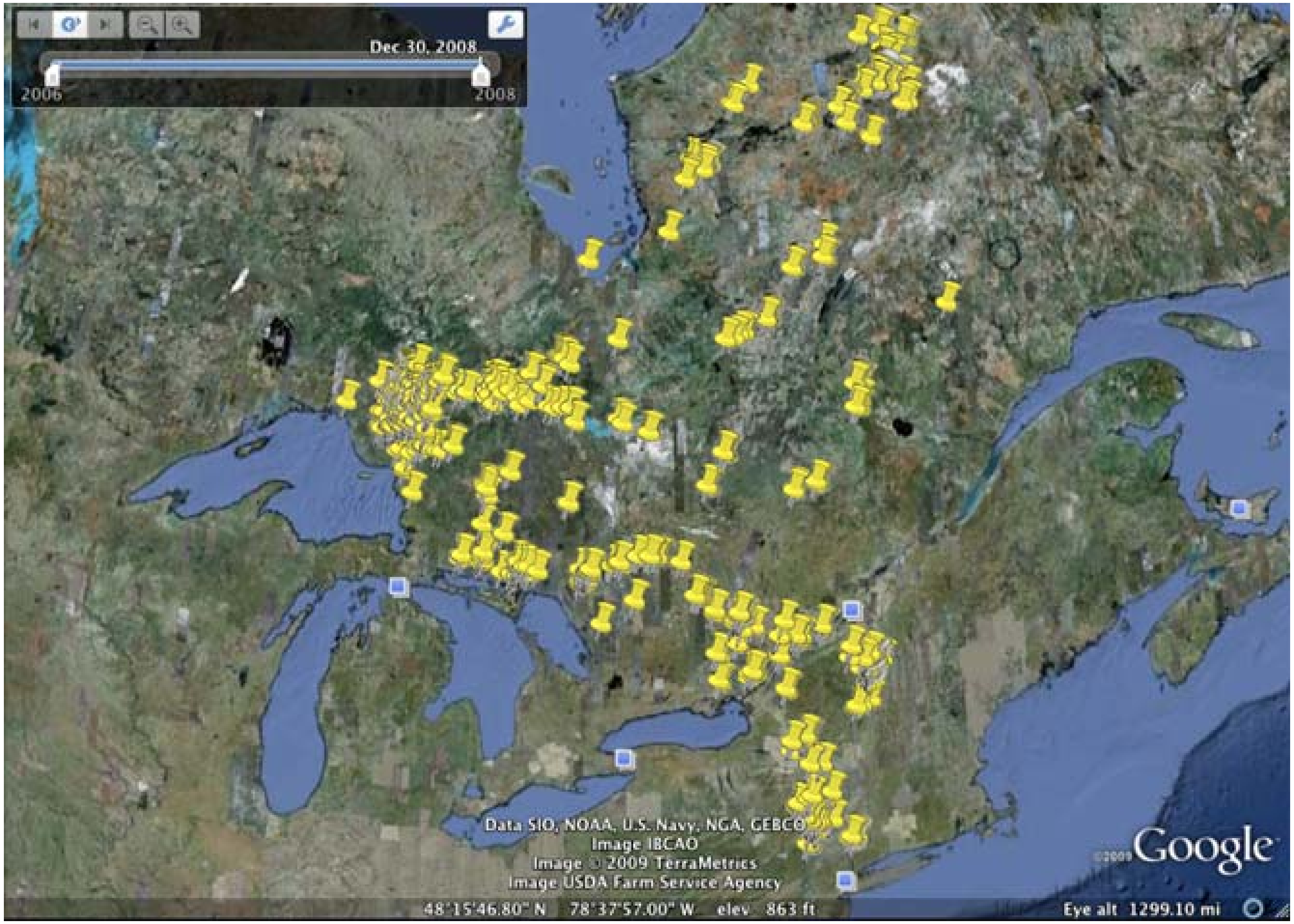
Period is more obvious in this binary sequence!

Algorithm General Framework

- **Detecting periods**: Use observation spots to find multiple interleaved periods
  - Observation spots are detected using **density-based method**
  - Periods are detected for each obs. spot using **Fourier Transform and auto-correlation**

- **Summarizing periodic behaviors:** via **clustering**
  - Give the statistical explanation of the behavior
  - E.g., “David has 80% probability to be at the office.”

Running Example: Bald Eager Migration



Real data of a bald eagle over 3 years

Method: Finding Observation Spots

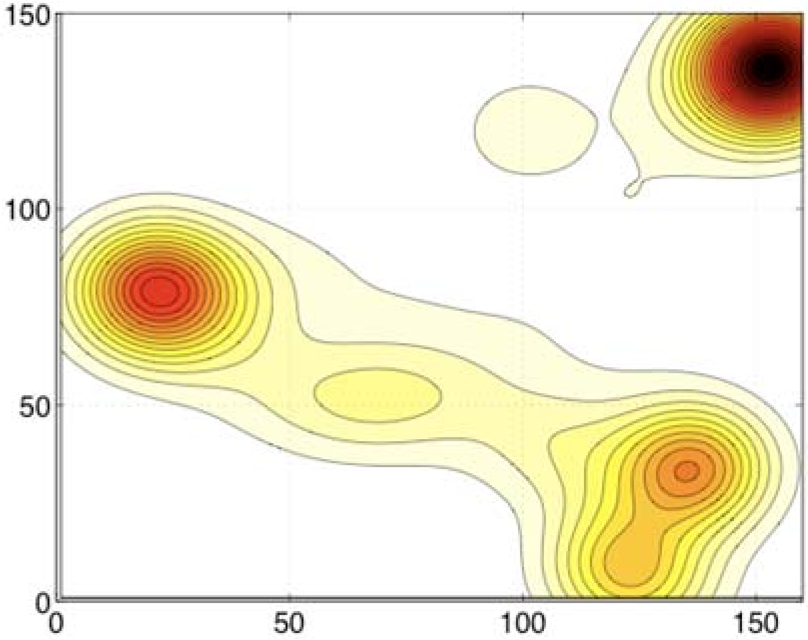
- Observation spots:
  - Frequently visited regions/locations
  - They should have higher density than a random location
- Partition the map into grids and use kernel-based method to find high density regions:

For each grid cell c, the density is estimated using the bivariate normal density kernel,

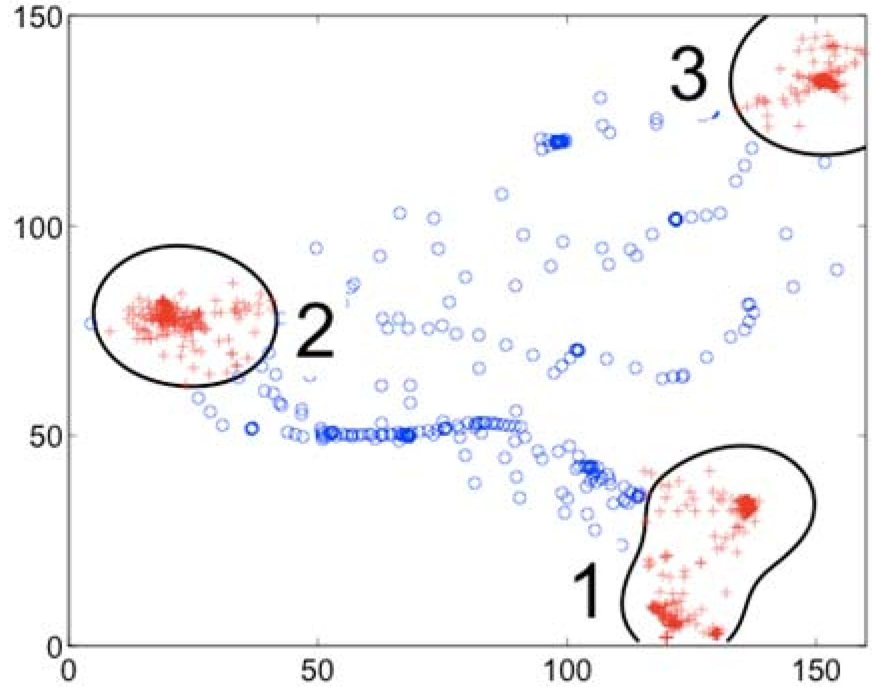
$$f(c) = \frac{1}{n\gamma^2} \sum_{i=1}^{n} \frac{1}{2\pi} \exp\left(-\frac{|c - loc_i|^2}{2\gamma^2}\right),$$

- Find the observation spots using the contour of high density places

Example: Finding Observation Spots



Density

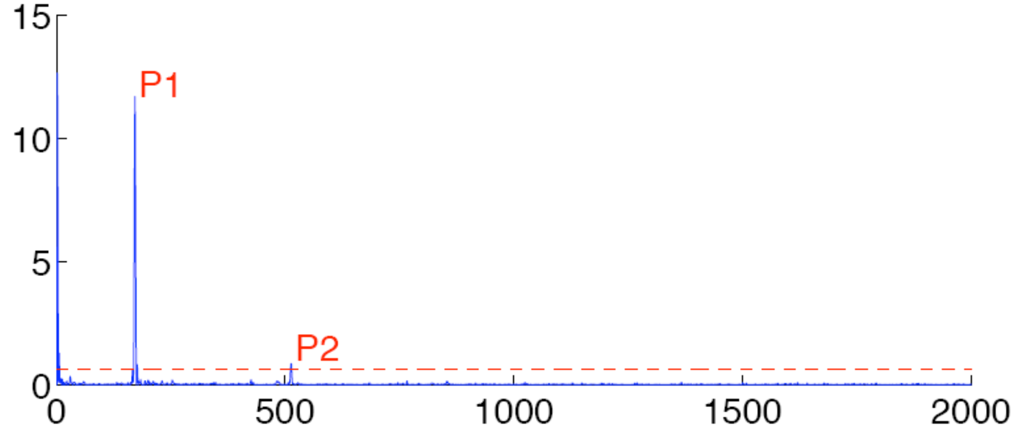


Observation spots

Period Detection for Each Observation Spot

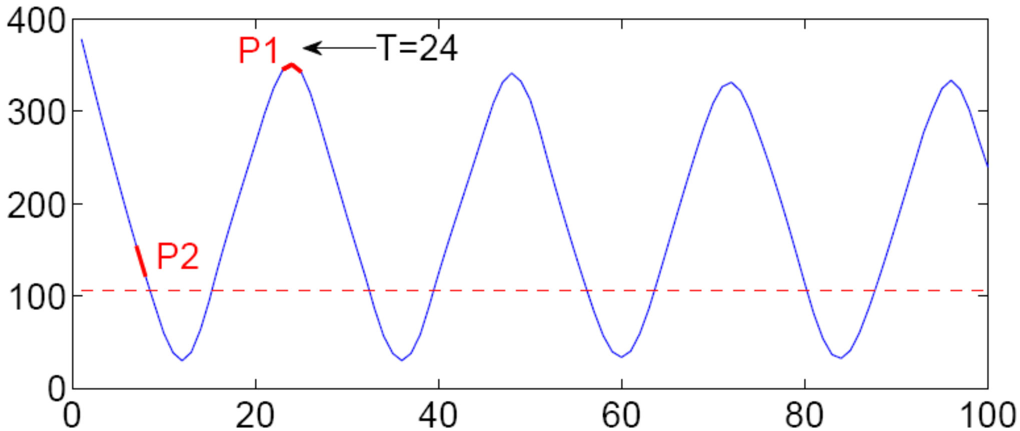
- For each observation spot, the movement is transformed into a binary sequence.
  - 0: not in the obs. spot
  - 1: in the obs. spot
- Use Fourier Transform combined with auto-correlation to find the periods

Example: Detect Periods for Each Obs. Spot



(a) Periodogram

Period candidates first detected using Fourier Transform



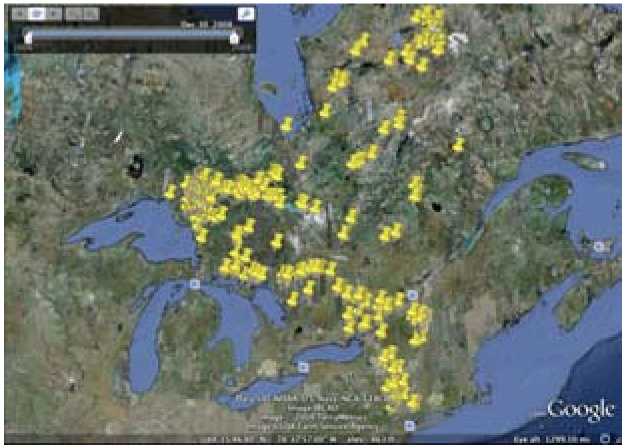
(b) Circular Autocorrelation

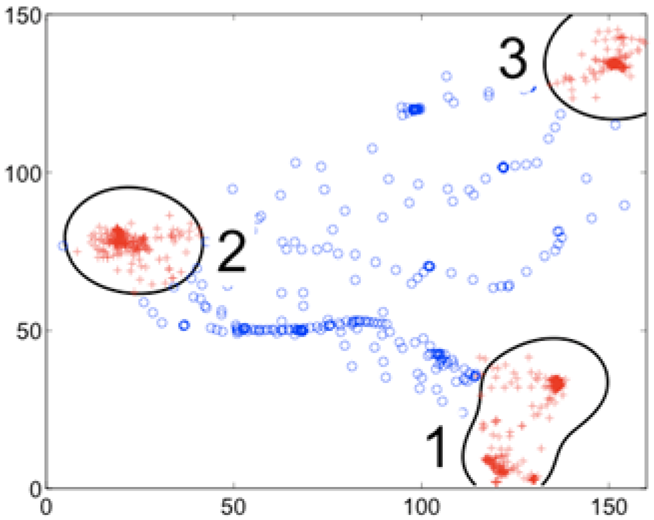
The exact period is further refined using circular autocorrelation

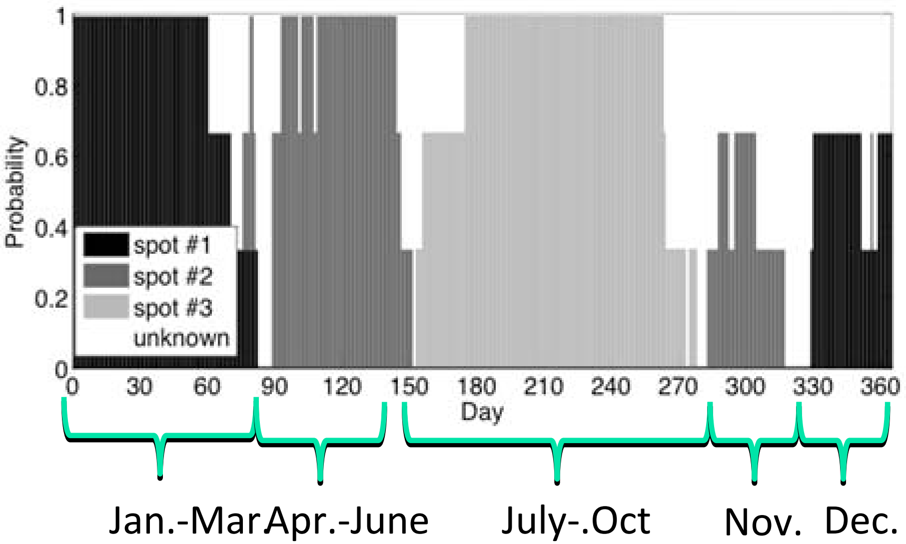
Summarizing Periodic Behaviors

- For each period, the movement is divided into segments
  - if the period is "day", each segment is a day
- Some segments during a time period form a periodic behavior
  - Daily behavior in summer
  - Daily behavior in winter
- To distinguish interleaved behavior, apply clustering on the segments
- A representative behavior is summarized over all the segments in a cluster

Example: Summarizing Periodic Behaviors







Part I. Moving Object Data Mining

- Introduction
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Clustering: Distance-Based vs. Shape-Based

- Distance-based clustering: Find a group of objects moving together
  - For whole time span
    - high-dimensional clustering
    - probabilistic clustering
  - For partial continuous time span
    - density-based clustering
    - moving cluster, flock, convoy *(borderline case between clustering and patterns)*
  - For partial discrete time span
    - swarm *(borderline case between clustering and patterns)*
- Shape-based clustering: Find similar shape trajectories
  - Variants of shape: translation, rotation, scaling, and transformation
  - Sub-trajectory clustering

High-Dimensional Clustering & Distance Measures

- Treat each timestamp as one dimension
- Many high-dimensional clustering methods can be applied to cluster moving objects
- Most popular high-dimensional distance measure
  - Euclidean distance
  - Dynamic Time Warping
  - Longest Common Subsequence
  - Edit Distance with Real Penalty
  - Edit Distance on Real Sequence

High-Dimensional Distance Measures

Distance Measure	Local Time Shifting	Noise	Metric	Complexity
Euclidean			✔	O(n)
DTW (Yi et al., ICDE'98)	✔			O(n^2)
LCSS (Vlachos et al., KDD'03)	✔	✔		O(n^2)
ERP (Chen et al., VLDB'04)	✔		✔	O(n^2)
EDR (Chen et al., SIGMOD'05)	✔	✔ (consider gap)		O(n^2)

Probabilistic Trajectory Clustering

(Gaffney et al., KDD'00; Chudova et al., KDD'03)

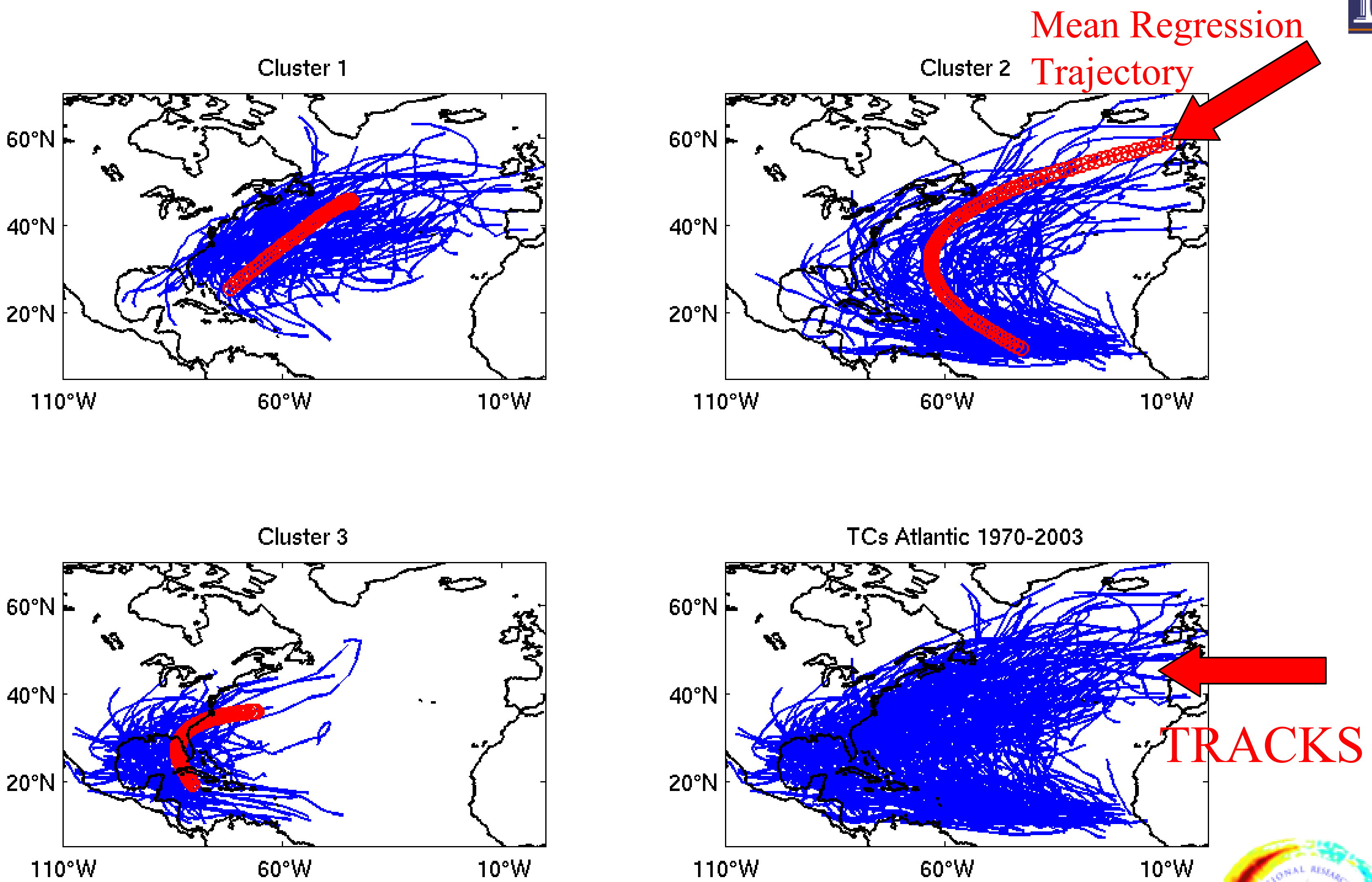
- Basic assumption: Data produced in the following ***generative*** manner
  - An individual is drawn randomly from the population of interest
  - The individual has been assigned to a cluster k with probability w_k, $\sum_{k=1}^{K} w_k = 1$, these are the *prior* weights on the K clusters
  - Given that an individual belongs to a cluster k, there is a density function $f_k(y_j \mid \theta_k)$ which generates an observed data item y_j for the individual j
- The probability density function of observed trajectories is a mixture density

$$P(y_j \mid x_j, \theta) = \sum_{k}^{K} f_k(y_j \mid x_j, \theta_k) w_k$$

  - $f_k(y_j \mid x_j, \theta_k)$ is the density component
  - w_k is the weight, and θ_k is the set of parameters for the k-th component
- θ_k and w_k can be estimated from the trajectory data using the *Expectation-Maximization* (*EM*) algorithm

Clustering Results For Hurricanes

(Camargo et al. 06)

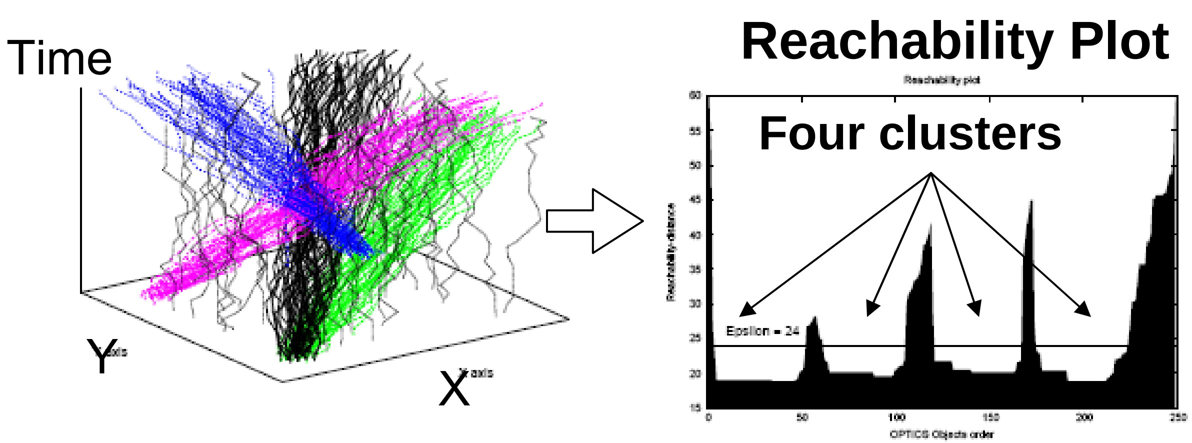


Tracks Atlantic named Tropical Cyclones 1970-2003.

Density-Based Trajectory Clustering

(M. Nanni & D. Pedreschi, JIIS'06)

- Define the distance between *whole* trajectories
  - A trajectory is represented as a sequence of location and timestamp
  - The distance between trajectories is the average distance between objects for every timestamp
- Use the OPTICS algorithm for trajectories
  - e.g.,



Temporal Focusing: TF-OPTICS

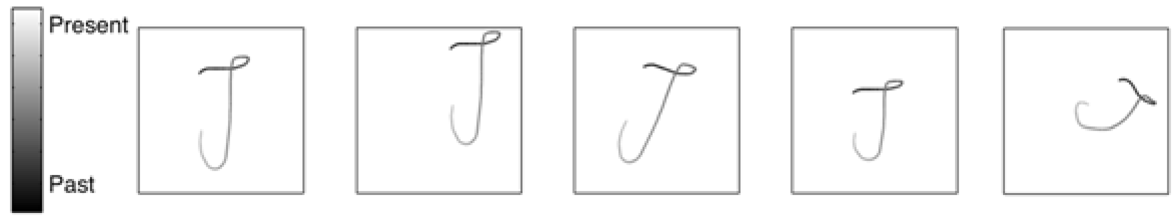
(M. Nanni & D. Pedreschi, JIIS'06)

- In a real environment, not all time intervals have the same importance
  - e.g., *in rush hours*, many people move from home to work or vice versa
- Clustering trajectories only in meaningful time intervals can produce more interesting results
- *TF-OPTICS* aims at **searching the most meaningful time intervals**, which allows us to isolate the clusters of higher quality
- Method:
  - Define the quality of a clustering
    - Take account of both high-density clusters and low-density noise
    - Can be computed directly from the reachability plot
  - Find the time interval that maximizes the quality
    1. Choose an initial random time interval
    2. Calculate the quality of neighborhood intervals generated by increasing or decreasing the starting or ending times
    3. Repeat Step 2 as long as the quality increases

Invariant Distance Measures for Trajectories
(Vlachos et al., KDD'04)

- Invariants: Translation, Rotation, Scaling, Transformation

Similar trajectories in different invariants



(a) (b) (c) (d) (e)

- Map each trajectory to a trajectory in a rotation invariant space.
  - Movement vector: $V_t = P_t - P_{t-1}, \quad t = 1, \ldots, n-1$
  - angles of each movement vector is *relative* to a reference vector
  - Angle/Arc-Length pairs (AAL)

$$P_{AAL} = [(\hat{V_1}, \frac{\|V_1\|}{\sum_i \|V_i\|}), \ldots, (\hat{V_{n-1}}, \frac{\|V_{n-1}\|}{\sum_i \|V_i\|})]$$

- Use Dynamic Time Warping (DTW) to measure the distance in invariant space

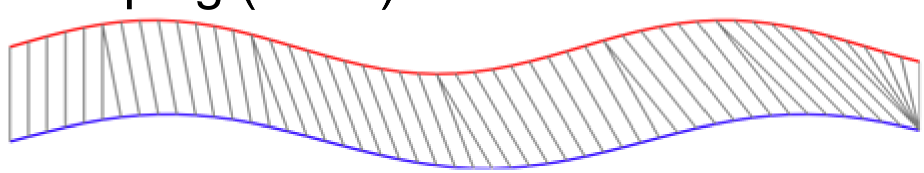
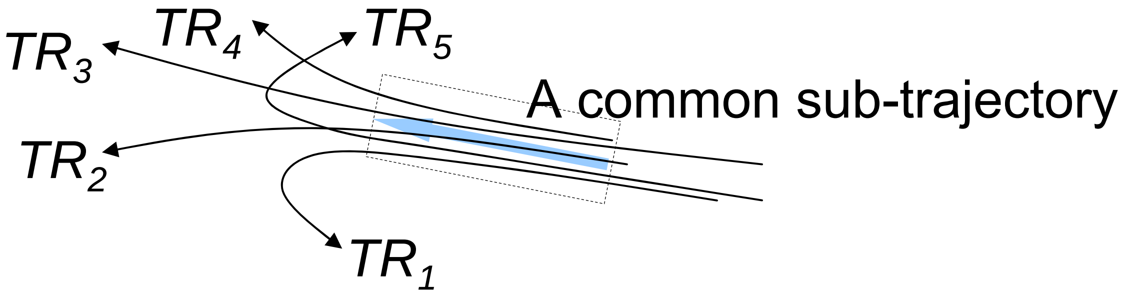


Figure 7: Elastic matching achieved by DTW.

Trajectory Clustering: A Partition-and-Group Framework (Lee et al., SIGMOD'07)

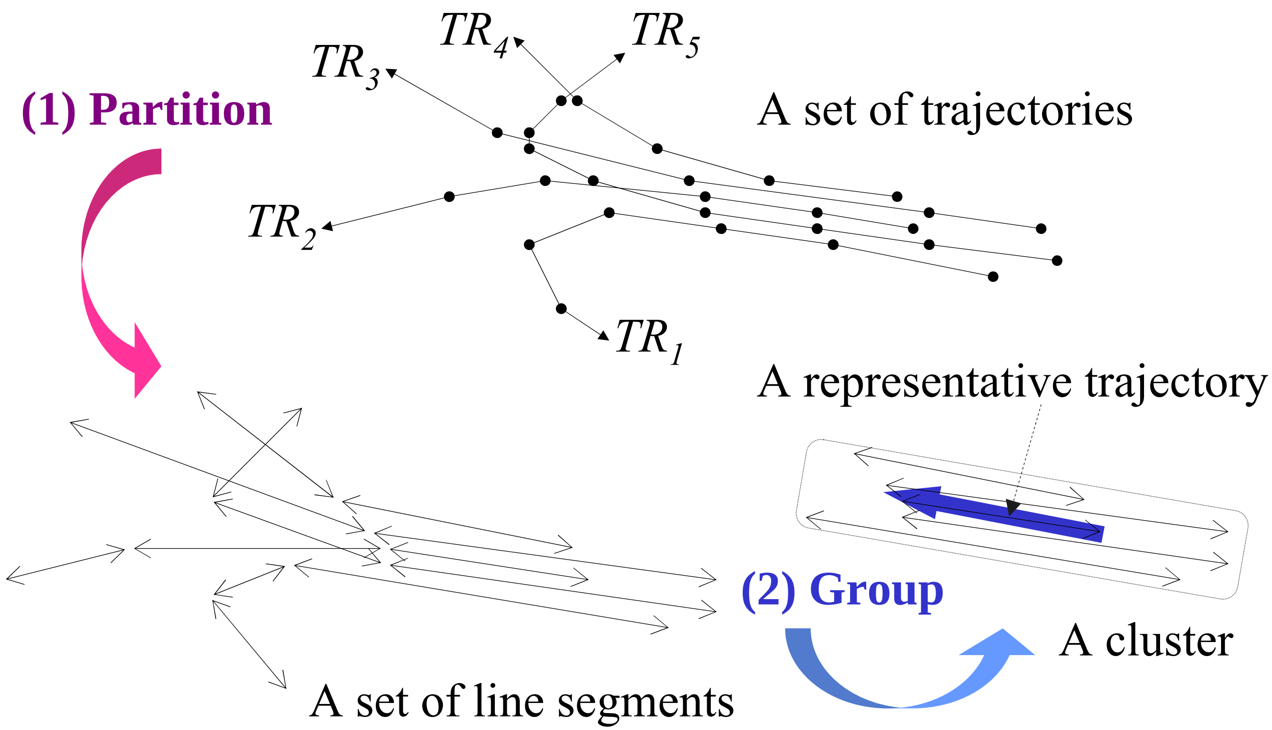
- Existing algorithms group trajectories ***as a whole*** ⇒ They might not be able to find ***similar portions*** of trajectories
  - e.g., common behavior cannot be discovered since TR_1~TR_5 move to totally different directions



- ***Partition-and-group:*** discovers common ***sub***-trajectories
- Usage: Discover ***regions of special interest***
  - *Hurricane Landfall Forecasts:* Discovery of common behaviors of hurricanes ***near the coastline*** or ***at sea*** (*i.e.*, before landing)
  - *Effects of Roads and Traffic on Animal Movements: Discover* common behaviors of animals ***near the road***

Partition-and-Group: Overall Procedure

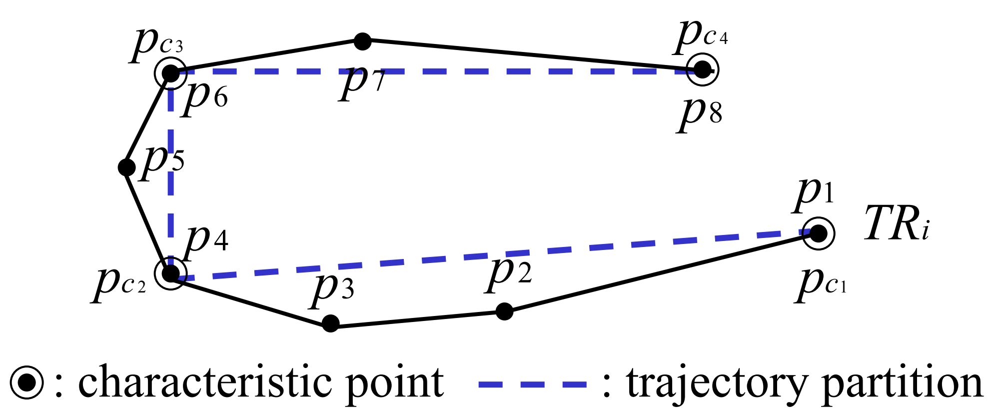
- Two phases: ***partitioning*** and ***grouping***



Note: A representative trajectory is a common sub-trajectory

The Partitioning Phase

- Identify the points where the behavior of a trajectory changes rapidly ⇒ *characteristic points*
  - An optimal set of characteristic points is found by using the minimum description length (MDL) principle



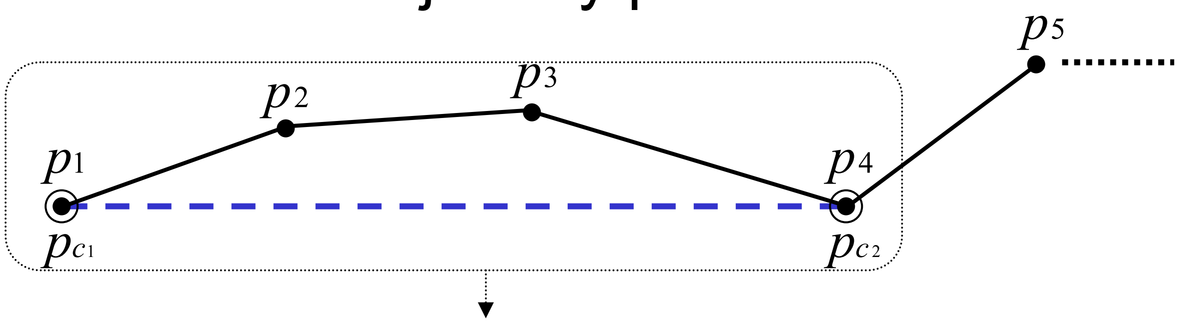
- Partition a trajectory at every characteristic point

Overview of the MDL Principle

- The MDL principle has been widely used in information theory
- The MDL cost consists of two components: ***L*(*H*)** and ***L*(*D*|*H*)**, where *H* means the hypothesis, and *D* the data
  - $L(H)$ is the length, in bits, of the description of the hypothesis
  - $L(D|H)$ is the length, in bits, of the description of the data when encoded with the help of the hypothesis
- The best hypothesis *H* to explain *D* is the one that minimizes the sum of $L(H)$ and $L(D|H)$

MDL Formulation

- Finding the optimal partitioning translates to finding the best hypothesis *using the MDL principle*
  - *H* → a set of trajectory partitions, *D* → a trajectory
  - *L*(*H*) → the sum of the length of all trajectory partitions
  - *L*(*D*|*H*) → the sum of the difference between a trajectory and a set of its trajectory partitions



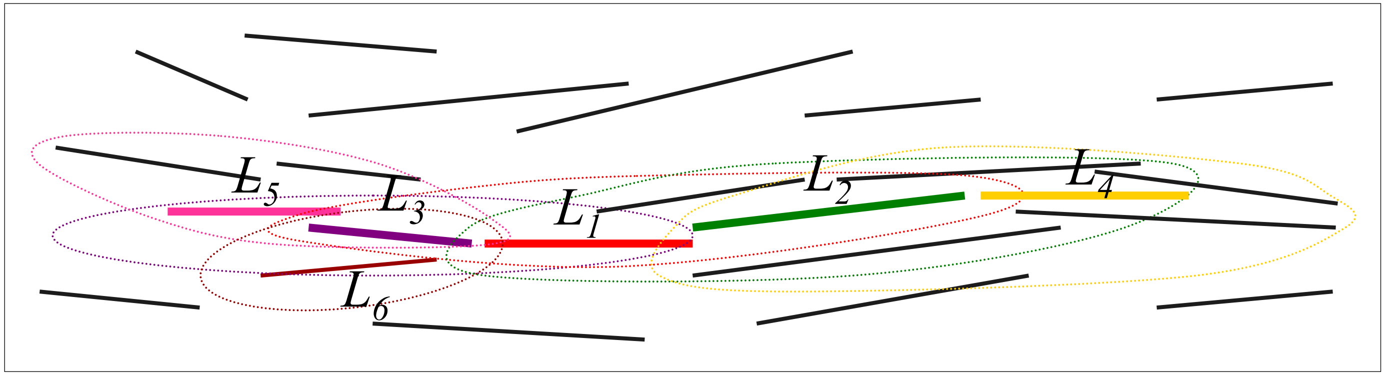
$$
\begin{aligned}
L(H) &= \log_2(len(p_1p_4)) \\
L(D\,|\,H) &= \log_2(d_\perp(p_1p_4, p_1p_2) + d_\perp(p_1p_4, p_2p_3) + d_\perp(p_1p_4, p_3p_4)) + \\
&\quad\ \log_2(d_\theta(p_1p_4, p_1p_2) + d_\theta(p_1p_4, p_2p_3) + d_\theta(p_1p_4, p_3p_4))
\end{aligned}
$$

- *L*(*H*) measures *conciseness*; *L*(*D*|*H*) *preciseness*

Grouping Phase (1/2)

- Find the clusters of trajectory partitions using density-based clustering (*i.e.*, DBSCAN)
  - A density-connect component forms a cluster, *e.g.*, $\{ L_1, L_2, L_3, L_4, L_5, L_6 \}$

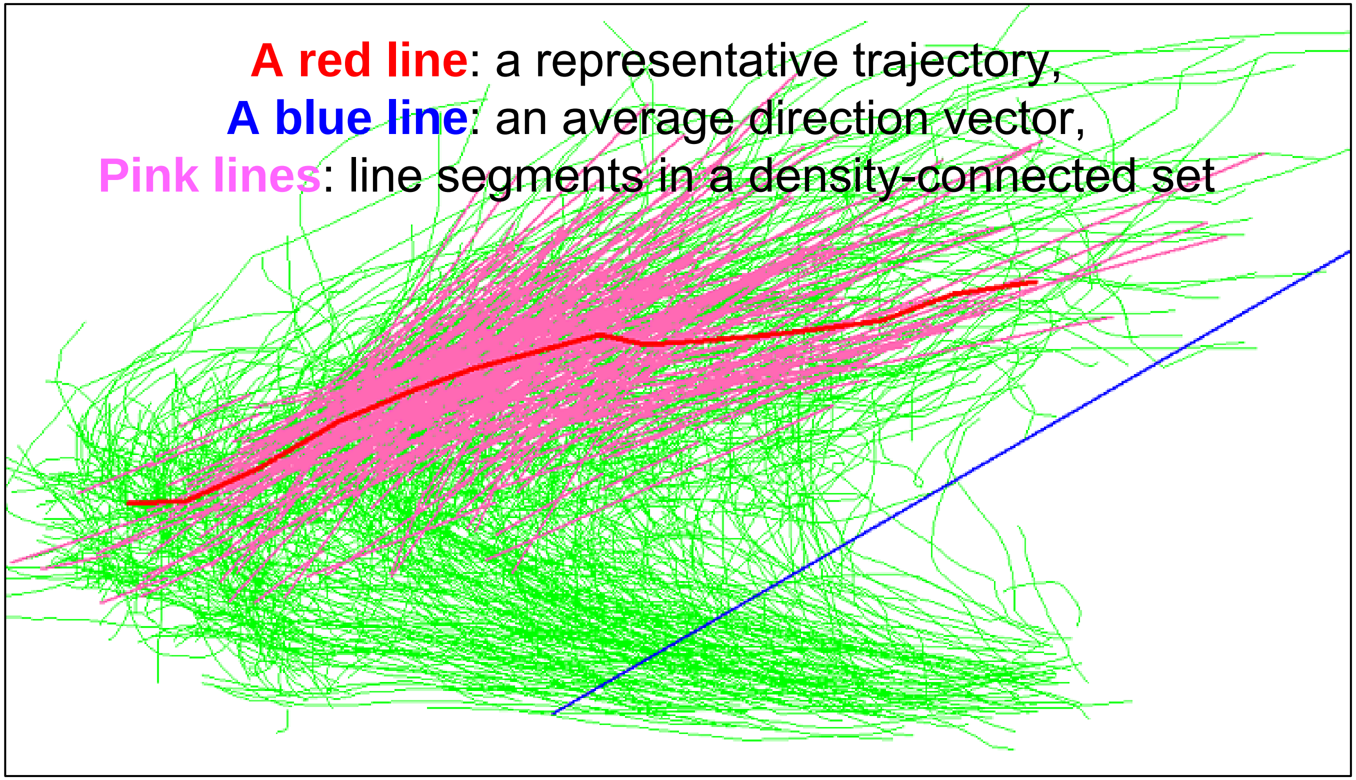
$MinLns = 3$



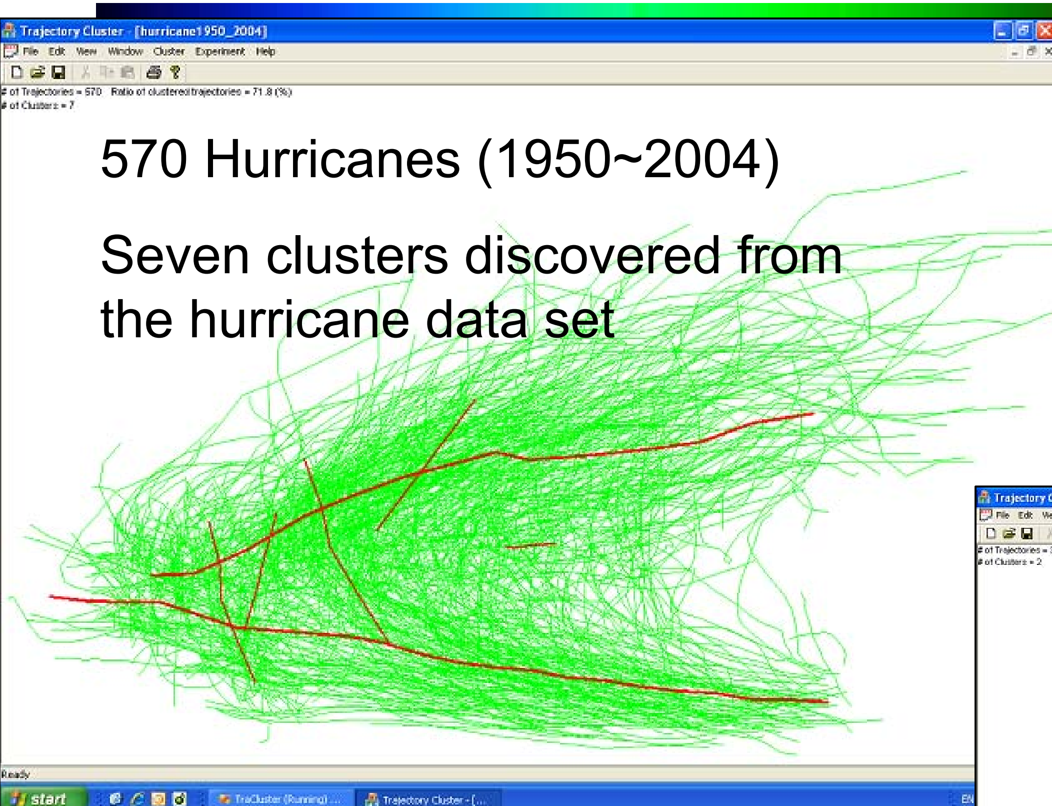
$$L_6 \quad L_5 \longleftrightarrow L_3 \longleftrightarrow L_1 \longleftrightarrow L_2 \longleftrightarrow L_4$$

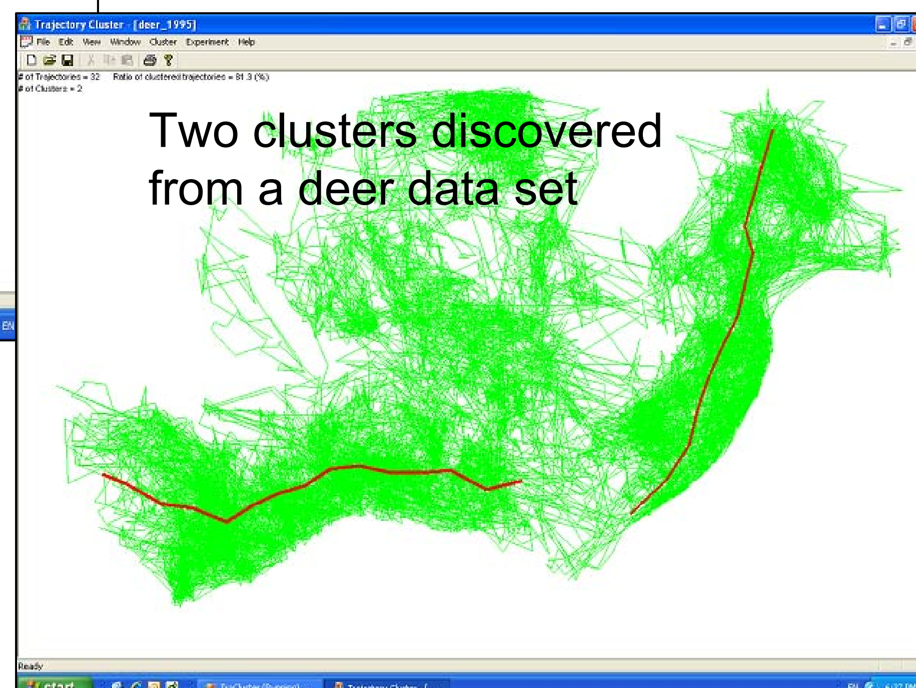
Grouping Phase (2 / 2)

- Describe the overall movement of the trajectory partitions that belong to the cluster



Example: Trajectory Clustering Results





Red line: a representative trajectory

Part I. Moving Object Data Mining

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Location Prediction for Moving Objects

- Predicting future location
  - Based on its own history of one moving object
    - Linear (not practical) vs. non-linear motion (more practical)
    - Vector based (predict near time, e.g., next minute) vs. pattern based (predict distant time, e.g., next month/year)
  - Based on all moving objects' trajectories
    - based on frequent patterns

Recursive Motion Function

(Tao et al., SIGMOD'04)

- Non-linear model, near time prediction, vector-based method
- Linear model is not practical in prediction, so better to use non-linear model
- Recursive motion function

  $$\boldsymbol{o}(t) = \mathbf{C}_1 \cdot \boldsymbol{o}(t-1) + \mathbf{C}_2 \cdot \boldsymbol{o}(t-2) + \ldots + \mathbf{C}_f \cdot \boldsymbol{o}(t-f)$$

  C_i is a constant matrix expressing several complex movement types, including polynomials, ellipse, sinusoids, etc.

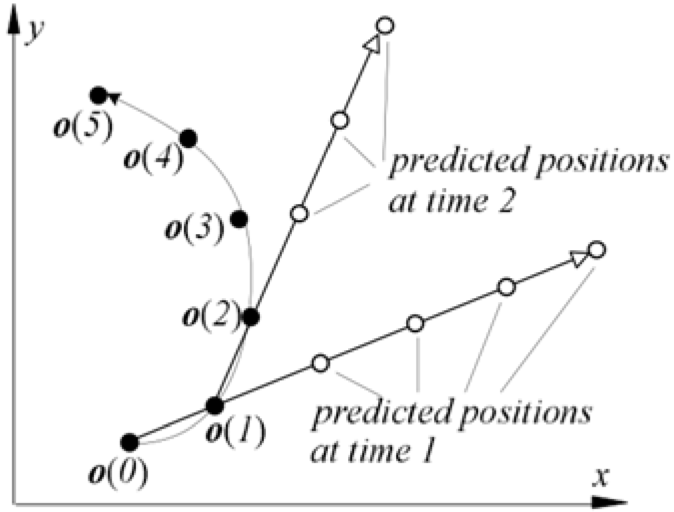
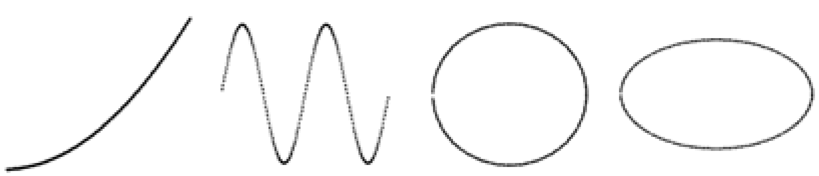


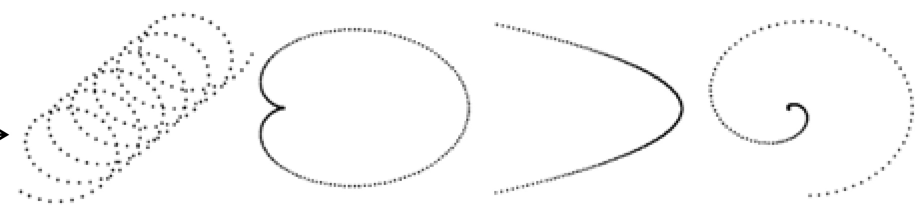
Figure 1.1: Failure of linear prediction

- Use basic motion matrices to model unknown motion matrices



(a) Polynomial (b) Sinusoid (c) Circle (d) Ellipse

Figure 6.1: Movements with known motion matrices

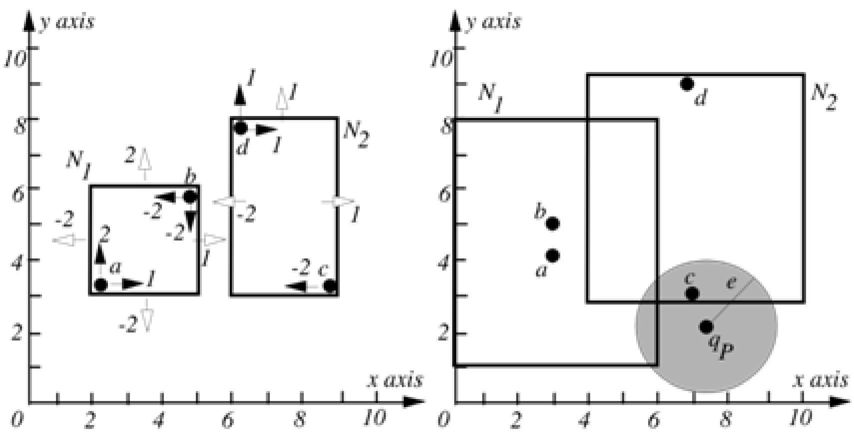


(a) Spiral (b) Peach (c) Parabola (d) Swirl

Figure 6.3: Movements with unknown motion matrices

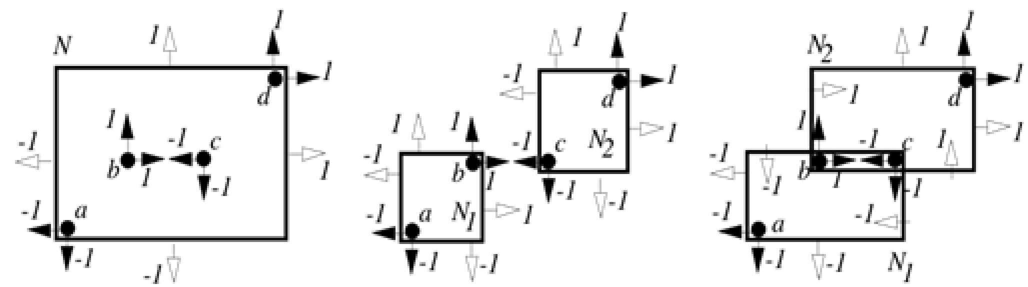
Efficient Implementation: Recursive Motion Prediction

- Indexing expected trajectories using Spatio-Temporal Prediction Tree (STP-Tree)
- A combination of Time Parameterized R Tree (TPR-tree) and TPR*-tree



(a) MBRs & VBRs at time 0 (b) MBRs at time 1

Figure 2.2: Entry representations in a TPR-tree



(a) Node to split (b) Split on x-axis (c) Split on x-velocit

Figure 2.3: The split algorithm of the TPR*-tree

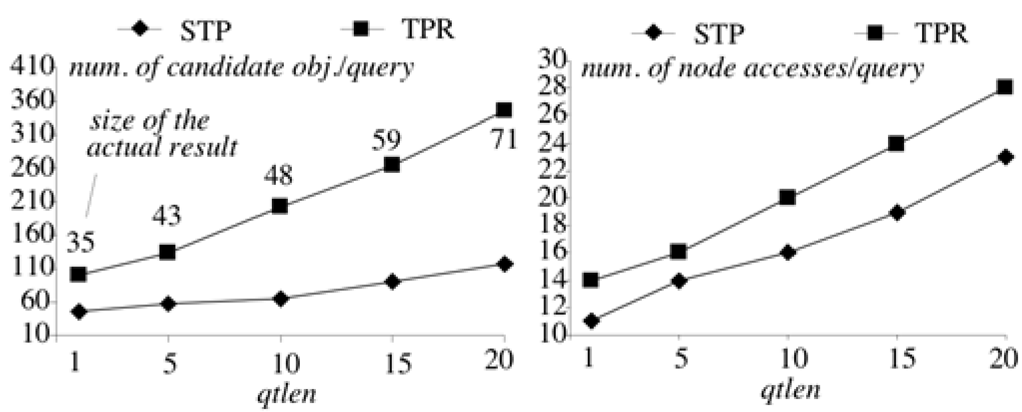
Experimental Results: Recursive Motion Prediction

- Effectiveness (wrt retrospect)

(a) f=2 (b) f=3

Figure 6.5: Improvements in *peach* with larger retrospect

- Efficiency using STP-tree indexing



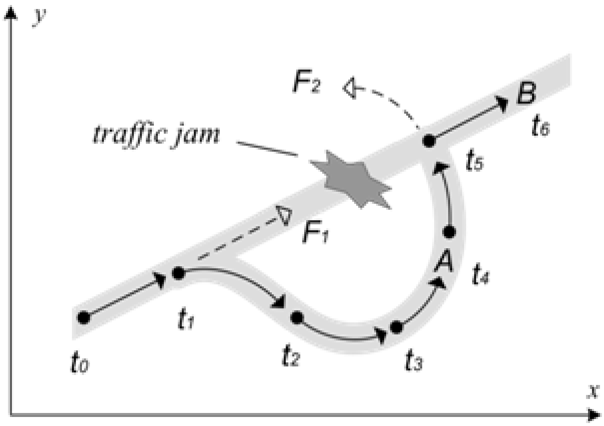
(a) Refinement cost (b) Server I/O cost

Figure 6.10: Query costs vs. *qtlen* (e=2.5%)

Hybrid Prediction (Jeung et al. , ICDE'08)

- Combining pattern and vector to prediction locations
- Can predict both distant and near time locations

  Ex: inadequate prediction using vector-based method



- Mining frequent periodic patterns

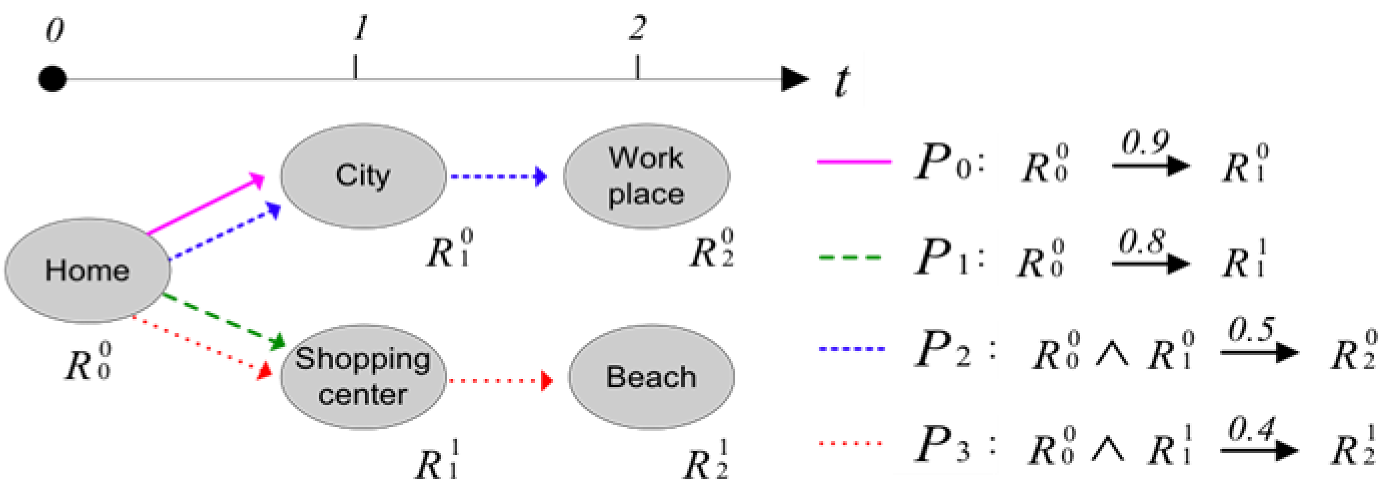
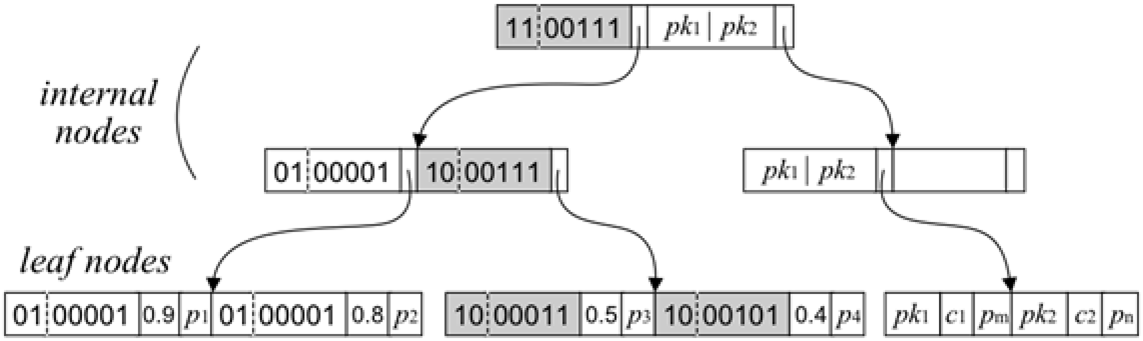


Fig. 3. An Example of Trajectory Patterns

Hybrid Prediction: Implementation and Predication

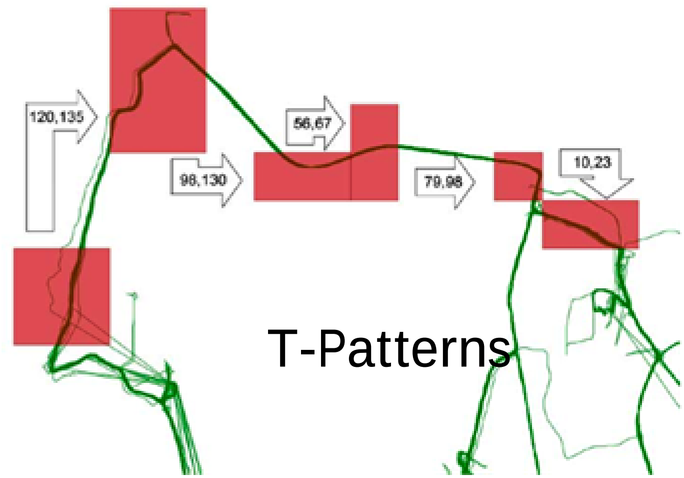
- Implementation: Indexing patterns using trajectory pattern tree

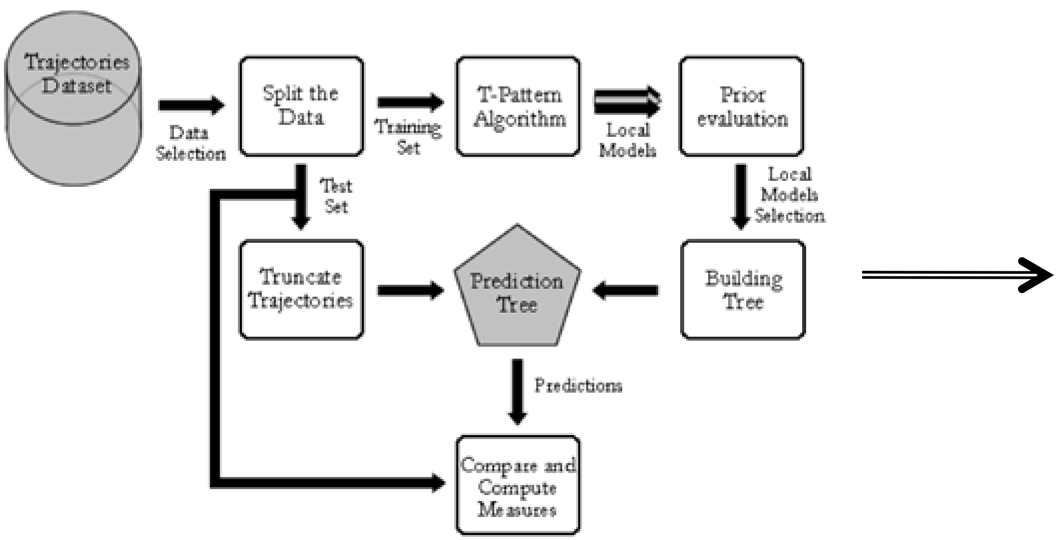


- Prediction:
  - For non-distant query, use Forward Query Processing to retrieve all the trajectory patterns
    - The premise of the trajectory pattern is similar to that of the query pattern key
    - its corresponding consequence time offset is the same as the query time
  - For distant query, use Backward Query Processing to retrieve patterns
    - Give up the premise key in FQP & relax time constraint

Prediction Using Frequent Trajectory Patterns (Monreale et al., KDD'09)

- Use frequent T-patterns of other moving objects
- If many moving objects follow a pattern, it is likely that a moving object will also follow this pattern
- Method
  - Mine T-Patterns
  - Construct T-Pattern Tree
  - Predict using T-pattern tree





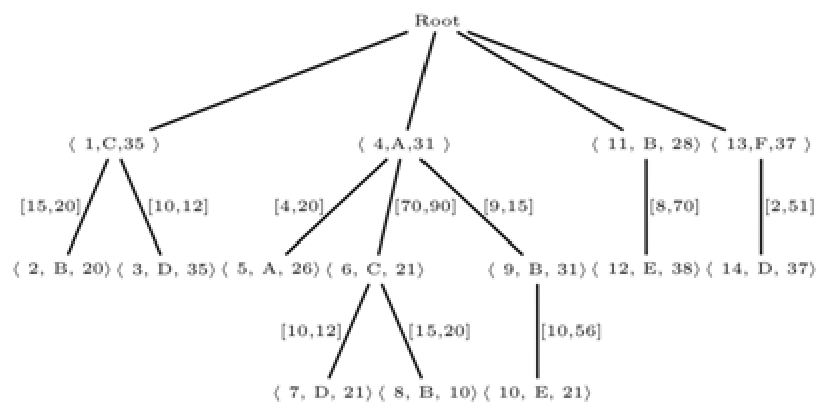


Figure 2: T-pattern Tree construction

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Trajectory Classification

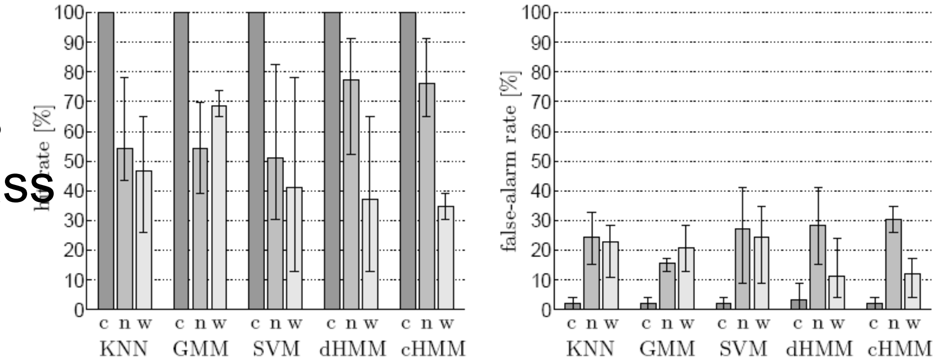
- Task: Predict the class labels of moving objects based on their trajectories and other features
- Two approaches
  - Machine learning techniques
    - Studied mostly in pattern recognition, bioengineering, and video surveillance
    - The hidden Markov model (HMM)
  - Trajectory-based classification (**TraClass**): Trajectory classification using hierarchical region-based and trajectory-based clustering

Machine Learning for Trajectory Classification (Sbalzarini et al. 02)

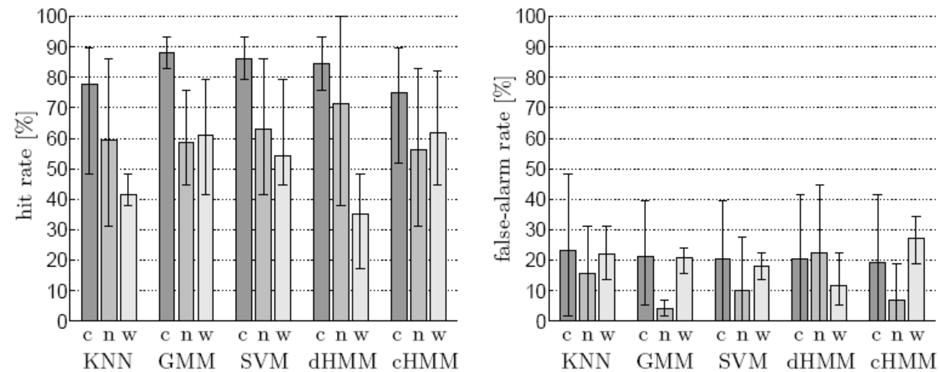
- Compare various machine learning techniques for biological trajectory classification
- Data encoding
  - For the hidden Markov model, a whole trajectory is encoded to a sequence of the momentary speed
  - For other techniques, a whole trajectory is encoded to the mean and the minimum of the speed of a trajectory, thus a vector in $\mathbf{R}^2$
- Two 3-class datasets: Trajectories of living cells taken from the scales of the fish Gillichthys mirabilis
  - Temperature dataset: 10° C, 20° C, and 30° C
  - Acclimation dataset: Three different fish populations

Machine Learning Techniques Used

- *k*-nearest neighbors (KNN)
  - A previously unseen pattern *x* is simply assigned to the same class to which the majority of its *k*-nearest neighbors belongs
- Gaussian mixtures with expectation maximization (GMM)
- Support vector machines (SVM)
- Hidden Markov models (HMM)
  - **Training**: Determine the model parameters λ = (A, B, π) to maximize *P* [*x* | λ] for a given observation *x*



Temperature data set



Acclimation data set

  - **Evaluation**: Given an observation x = { O_1, …, O_T } and a model λ = (A, B, π), compute the probability *P* [x | λ] that the observation *x* has been produced by a source described by λ

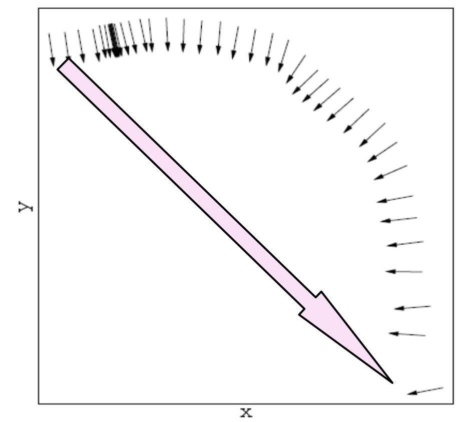
Vehicle Trajectory Classification
(Fraile and Maybank 98)

- The measurement sequence is divided into overlapping segments
- In each segment, the trajectory of the car is approximated by a smooth function and then assigned to one of four categories: *ahead*, *left*, *right*, or *stop*
- The list of segments is reduced to a string of symbols drawn from the set {*a*, *l*, *r*, *s*}
- The string of symbols is classified using the hidden Markov model (HMM)

Use of the HMM for Classification

- Classification of the global motions of a car is carried out using an HMM
- The HMM contains *four* states which are in order ***A***, ***L***, ***R***, ***S***, which are the true states of the car: ahead, turning left, turning right, stopped
- The HMM has *four* output symbols in order ***a***, ***l***, ***r***, ***s***, which are the symbols obtained from the measurement segments
- The Viterbi algorithm is used to obtain the sequence of internal states

Measurement sequence



Observed symbols

s	s	s	s	s	s	s	s	s	s	s	s	s	s	s	s	r	r
a	a	a	r	r	r	r	a	a	a	a	r	r	r	r	r	r	a
S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	R	R
R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R	R

Sequence of inferred states

This measurement sequence means *the driver stops and then turns to the right*

Motion Trajectory Classification

(Bashir et al. 07)

- Motion trajectories
  - Tracking results from video trackers, sign language data measurements gathered from wired glove interfaces, and so on
- Application scenarios
  - Sport video (*e.g.*, soccer video) analysis
    - Player movements ⇒ A strategy
  - Sign and gesture recognition
    - Hand movements ⇒ A particular word
- The HMM-Based Algorithm
  1. Trajectories are segmented at points of change in curvature
  2. Sub-trajectories are represented by their Principal Component Analysis (PCA) coefficients
  3. The PCA coefficients are represented using a GMM for each class
  4. An HMM is built for each class, where the state of the HMM is a sub-trajectory and is modeled by a mixture of Gaussians

Use of the HMM for Classification

- Training and parameter estimation
  - The Baum-Welch algorithm is used to estimate the parameters
- Classification
  - The PCA coefficient vectors of input trajectories after segmentation are posed as an observation sequence to each HMM (*i.e.*, constructed for each class)
  - The maximum likelihood (ML) estimate of the test trajectory for each HMM is computed
  - The class is determined to be the one that has the largest maximum likelihood
- Experiment: Datasets
  - The Australian Sign Language dataset (ASL)
    - 83 classes (words), 5,727 trajectories
  - A sport video data set (HJSL)
    - 2 classes, 40 trajectories of high jump and 68 trajectories of slalom skiing objects
- Accuracy

Datasets	ASL #Classes : #Trajectories						HJSL
	2: 138	4: 276	8: 552	16: 1104	29: 2001	38: 2622	
HMM	0.96	0.92	0.86	0.78	0.69	0.66	0.91
GMM	0.98	0.89	0.85	0.74	0.67	0.64	0.90
PCA-DE [28]	0.94	0.93	0.83	0.73	0.56	0.62	0.45

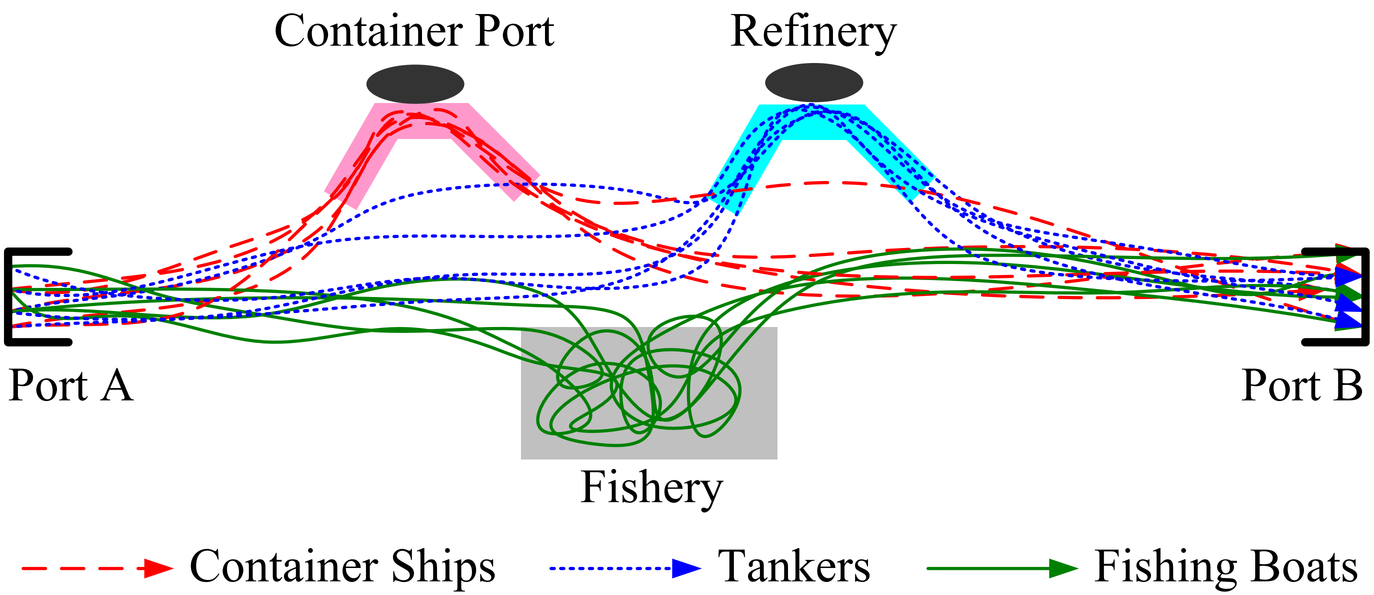
A Critique of Previous Methods

- Common Characteristics of Previous Methods: Use the ***shapes*** of ***whole*** trajectories to do classification
  - Encode a whole trajectory into a feature vector;
  - Convert a whole trajectory into a string or a sequence of the momentary speed; or
  - Model a whole trajectory using the HMM
- **Note**: Although a few methods segment trajectories, the main purpose is to approximate or smooth trajectories before using the HMM

TraClass: Trajectory Classification Based on Clustering

- Motivation
  - Discriminative features are likely to appear at ***parts*** of trajectories, not at whole trajectories
  - Discriminative features appear not only as common movement patterns, but also as ***regions***
- Solution
  - Extract features in a top-down fashion, first by ***region-based clustering*** and then by ***trajectory-based clustering***

Intuition and Working Example



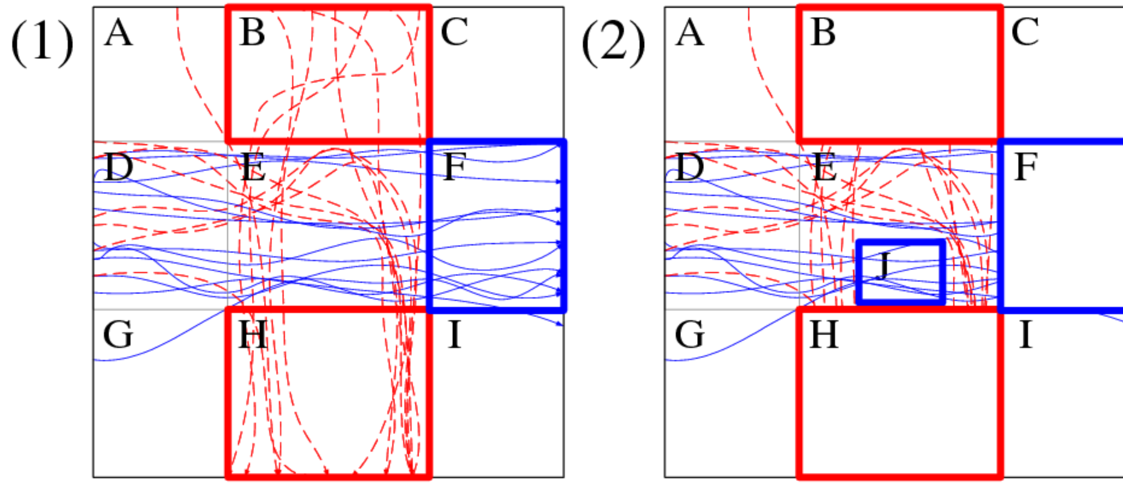
- Parts of trajectories near the container port and near the refinery enable us to distinguish between container ships and tankers even if they share common long paths
- Those in the fishery enable us to recognize fishing boats even if they have no common path there

Trajectory Partitions

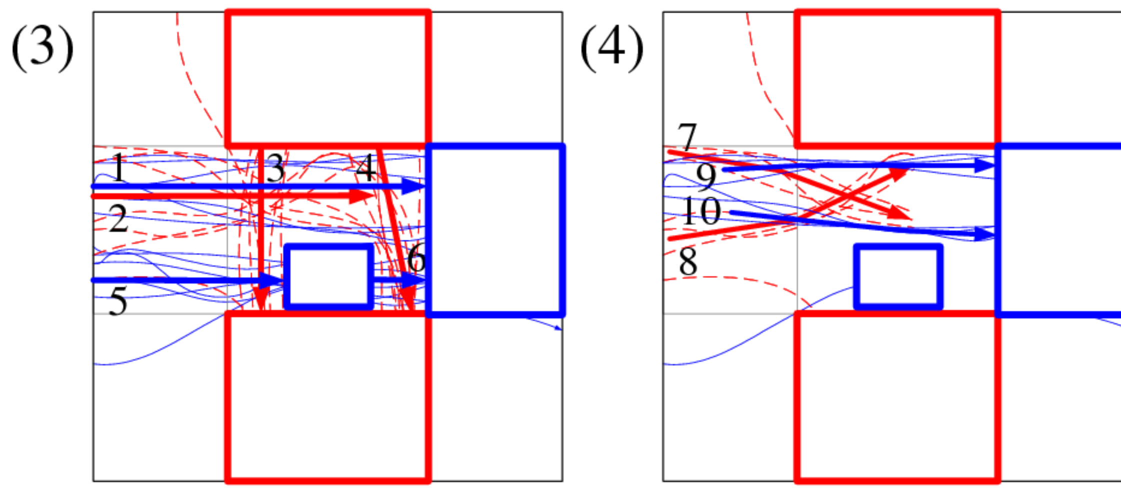
Region-Based Clustering

Trajectory-Based Clustering

Features



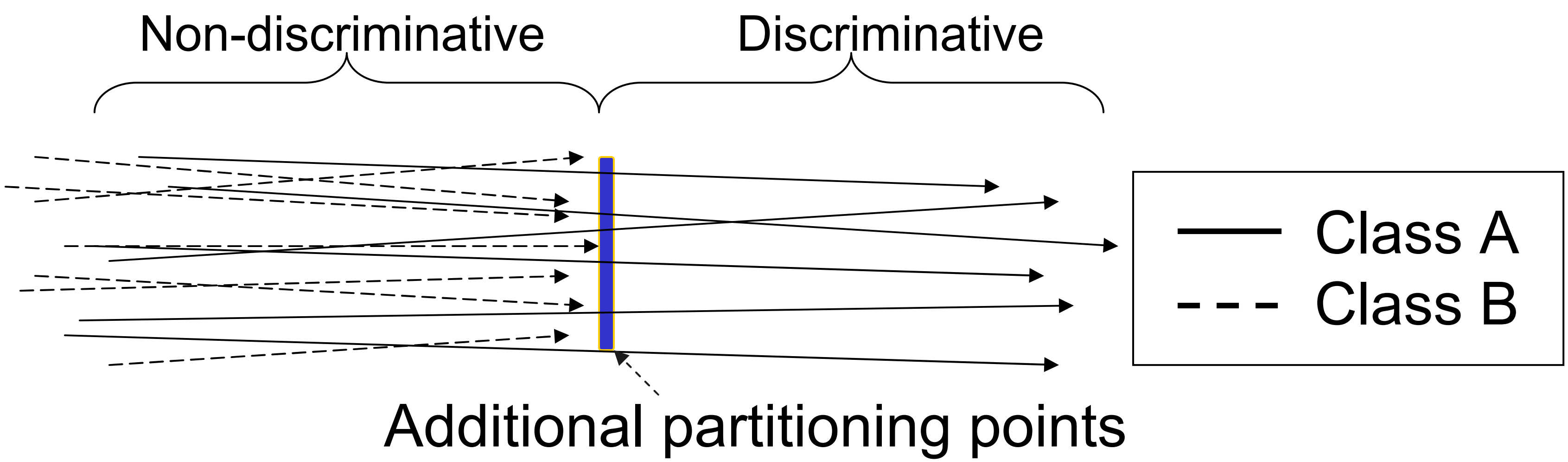
Region-Based Clustering



Trajectory-Based Clustering

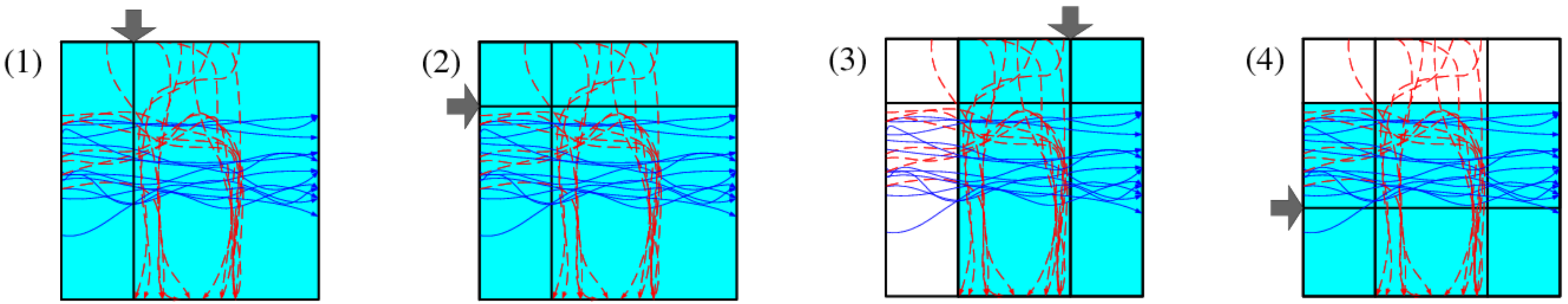
Class-Conscious Trajectory Partitioning

1. Trajectories are partitioned based on their shapes as in the partition-and-group framework
2. Trajectory partitions are further partitioned by ***the class labels***
   - The real interest here is to guarantee that trajectory partitions do not span the class boundaries



Region-Based Clustering

- Objective: Discover regions that have trajectories mostly of one class regardless of their movement patterns
- Algorithm: Find a better partitioning alternately for the X and Y axes as long as the MDL cost decreases
  - The MDL cost is formulated to achieve both homogeneity and conciseness

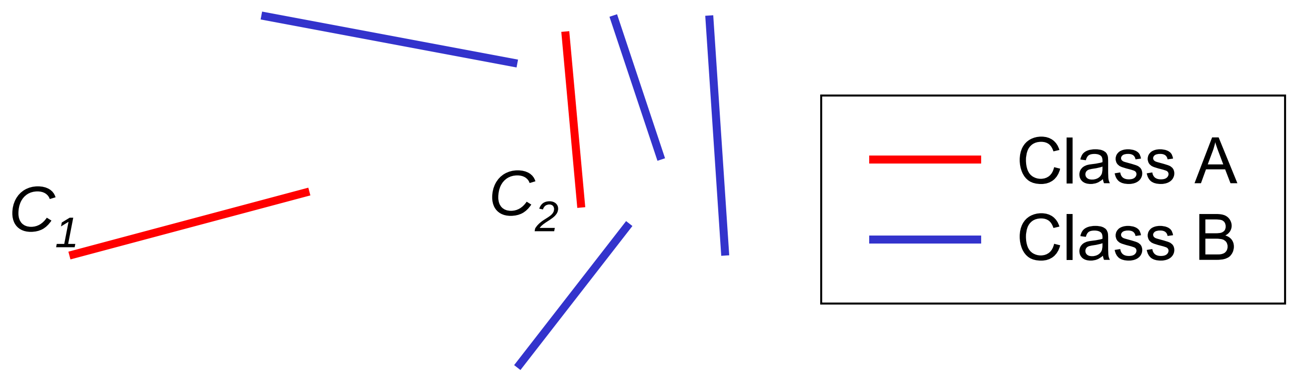


Trajectory-Based Clustering

- Objective: Discover sub-trajectories that indicate common movement patterns of each class
- Algorithm: Extend the partition-and-group framework for classification purposes so that the class labels are incorporated into trajectory clustering
  - If an ε-neighborhood contains trajectory partitions mostly of the same class, it is used for clustering; otherwise, it is discarded immediately

Selection of Trajectory-Based Clusters

- After trajectory-based clusters are found, highly *discriminative* clusters are selected for effective classification
  - If the average distance from a specific cluster to other clusters of *different classes* is high, the discriminative power of the cluster is high
  - e.g.,



C_1 is more discriminative than C_2

Overall Procedure of TraClass

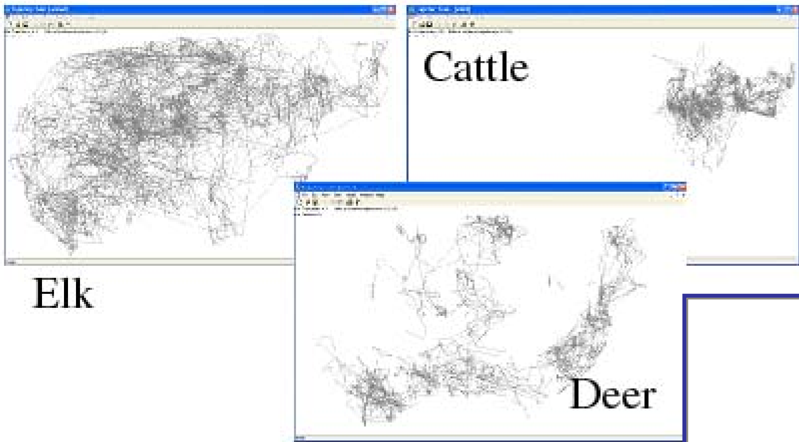
1. Partition trajectories
2. Perform region-based clustering
3. Perform trajectory-based clustering
4. Select discriminative trajectory-based clusters
5. Convert each trajectory into a feature vector
   - Each feature is either a region-based cluster or a trajectory-based cluster
   - The *i*-th entry of a feature vector is the frequency that the *i*-th feature occurs in the trajectory
6. Feed feature vectors to the SVM

Classification Results

- Datasets
  - Animal: Three classes ← three species: elk, deer, and cattle
  - Vessel: Two classes ← two vessels
  - Hurricane: Two classes ← category 2 and 3 hurricanes
- Methods
  - *TB-ONLY*: Perform trajectory-based clustering only
  - *RB-TB*: Perform both types of clustering
- Results

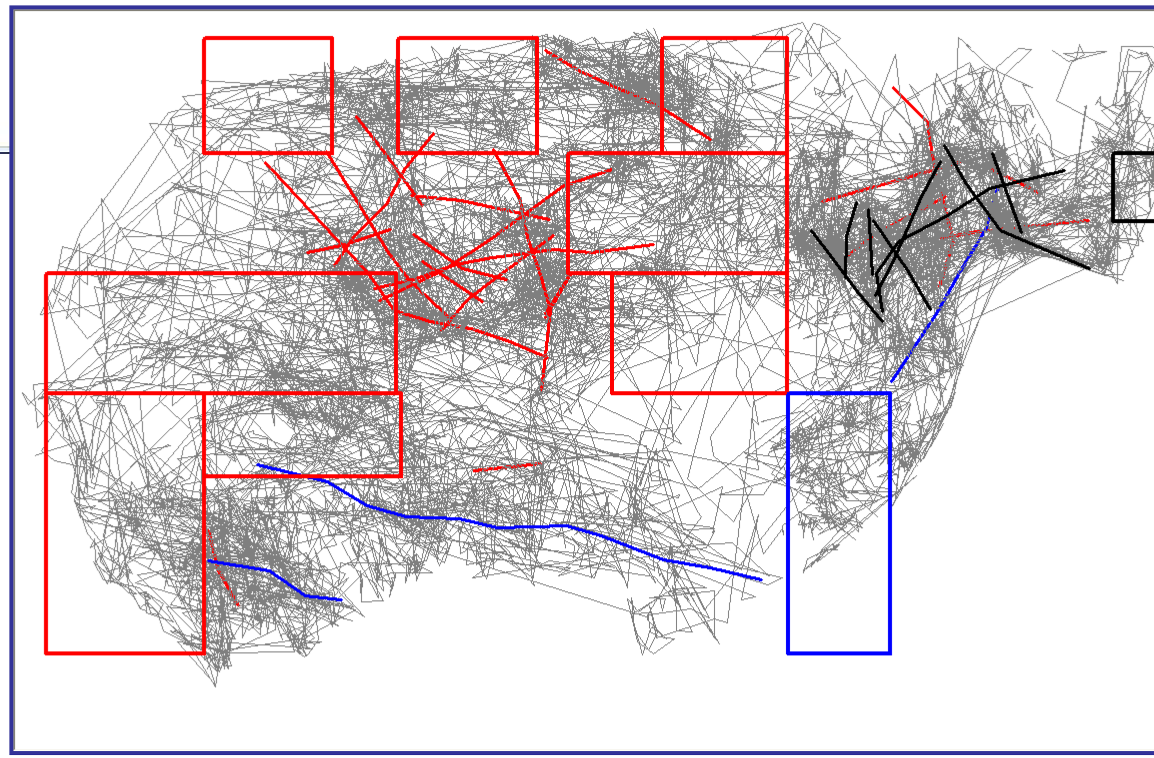
Data Set	Animal		Vessel		Hurricane	
Version	TB-ONLY	RB-TB	TB-ONLY	RB-TB	TB-ONLY	RB-TB
Accuracy (%)	50.0	83.3	84.4	98.2	65.4	73.1
Training Time (msec)	3542	2406	44683	22902	331	317
Prediction Time (msec)	104	98	722	608	48	46

Example: Extracted Features



Data (Three Classes)

Features:
10 Region-Based Clusters
37 Trajectory-Based Clusters



Accuracy = 83.3%

Part I. Moving Object Data Mining

- Introduction
- Movement Pattern Mining
- Periodic Pattern Mining
- Clustering
- Prediction
- Classification
- Outlier Detection

Trajectory Outlier Detection

- Task: Detect the trajectory outliers that are grossly different from or inconsistent with the remaining set of trajectories
- Methods and philosophy:

1. ***Whole*** trajectory outlier detection
    - A unsupervised method
    - A supervised method *based on classification*
2. Integration with multi-dimensional information
3. ***Partial*** trajectory outlier detection
    - A Partition-and-Detect framework

Outlier Detection: A Distance-Based Approach (Knorr et al. VLDBJ00)

- Define the distance between two *whole* trajectories
  - A whole trajectory is represented by

$$P = \begin{bmatrix} P_{start} \\ P_{end} \\ P_{heading} \\ P_{velocity} \end{bmatrix} \quad \text{where} \quad \begin{aligned} P_{start} &= (x_{start}, y_{start}) \\ P_{end} &= (x_{end}, y_{end}) \\ P_{heading} &= (avg_{heading}, max_{heading}, min_{heading}) \\ P_{velocity} &= (avg_{velocity}, max_{velocity}, min_{velocity}) \end{aligned}$$

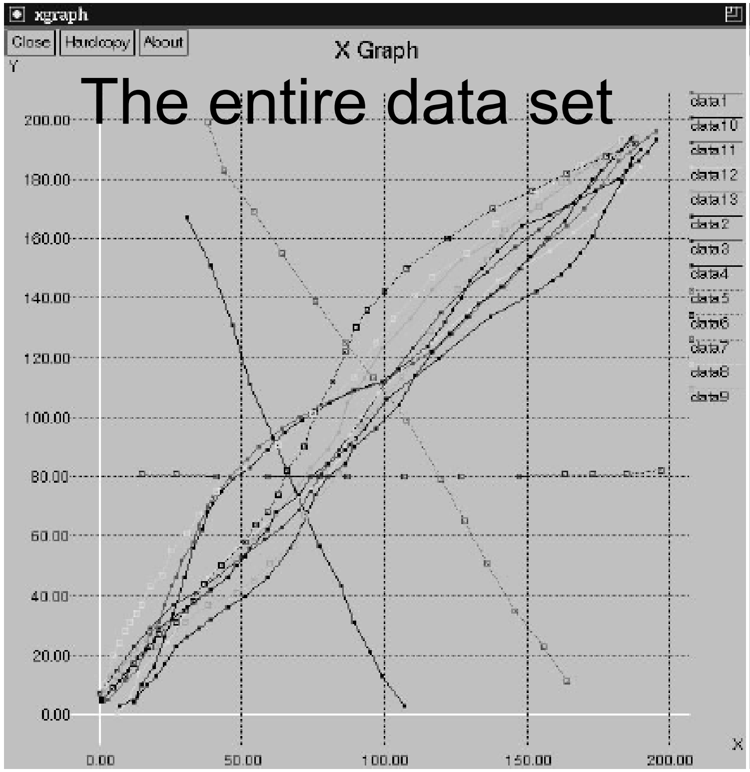
  - The distance between two whole trajectories is defined as

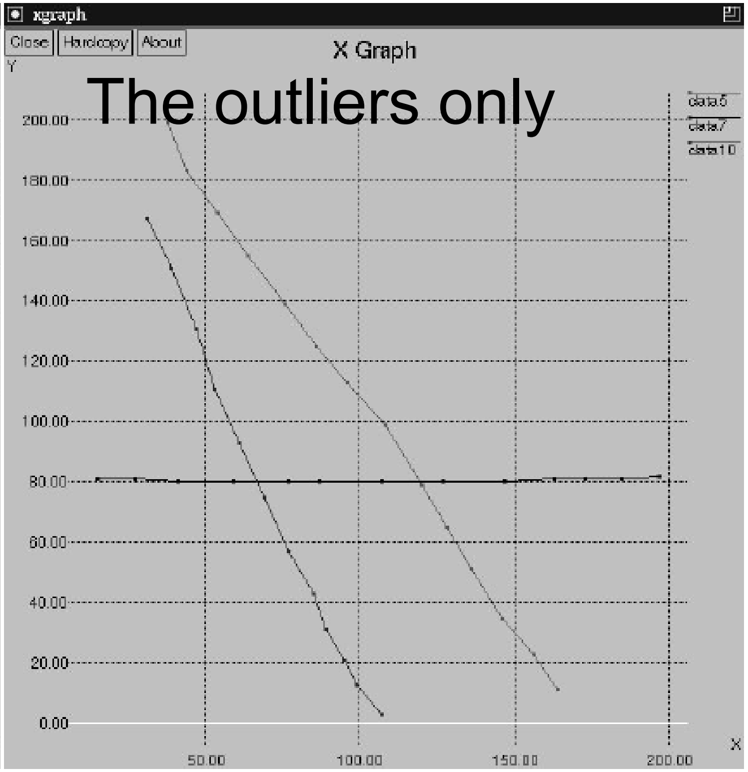
$$D(P_1, P_2) = \begin{bmatrix} D_{start}(P_1, P_2) \\ D_{end}(P_1, P_2) \\ D_{heading}(P_1, P_2) \\ D_{velocity}(P_1, P_2) \end{bmatrix} \cdot \begin{bmatrix} w_{start} & w_{end} & w_{heading} & w_{velocity} \end{bmatrix}$$

- Apply a distance-based approach to detection of trajectory outliers
  - An object *O* in a dataset *T* is a DB(*p*, *D*)-outlier if at least fraction *p* of the objects in *T* lies greater than distance *D* from *O*

Sample Trajectory Outliers

- Detect outliers from person trajectories in a room





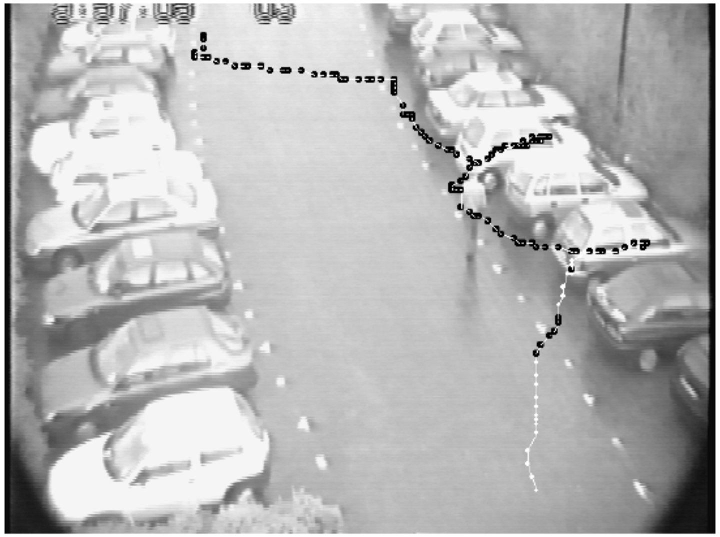
Use of Neural Networks (Owens and Hunter 00)

- A *whole* trajectory is encoded to a *feature vector*: $\mathbf{F} = [\ x, y, s(x), s(y), s(dx), s(dy), s(|d^2x|), s(|d^2y|)\ ]$
  - $s()$ indicates a time smoothed average of the quantity
  - $dx = x_t - x_{t-1}$
  - $d^2x = x_t - 2x_{t-1} + x_{t-2}$
- A self-organizing feature map (SOFM) is trained using the feature vectors of training trajectories, and a new trajectory is classified into novel (i.e., suspicious) or not novel
- ***Supervised learning***

An Application: Video Surveillance

- Training dataset: 206 normal trajectories
- Test dataset: 23 unusual and 16 normal trajectories
- Classification accuracy: 92%


An example of a normal trajectory

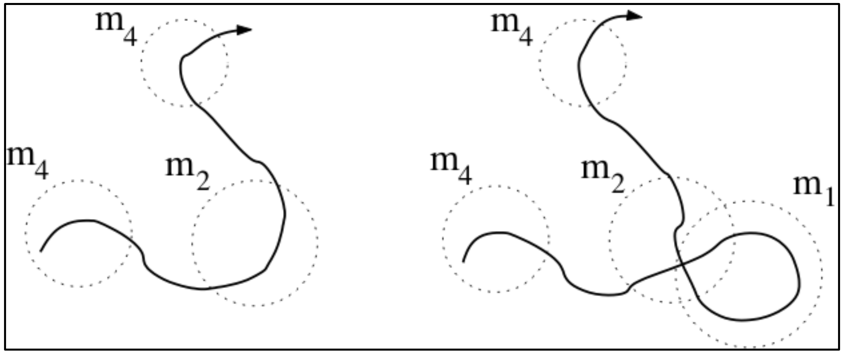

An unusual trajectory; The unusual points are shown in black

Anomaly Detection (Li et al. ISI'06, SSTD'07)

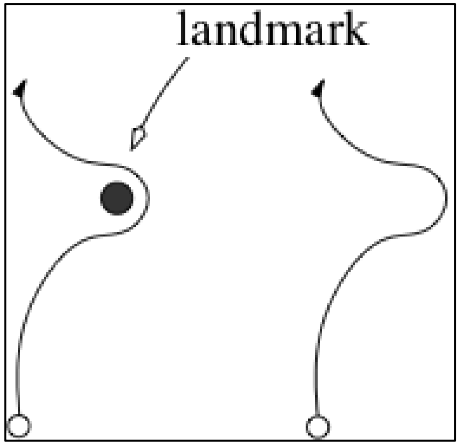
- Automated alerts of abnormal moving objects
- Current US Navy model: manual inspection
  - Started in the 1980s
  - 160,000 ships

Conditional Anomalies and Motif Representations

- Raw analysis of collected data does not fully convey "anomaly" information
- More effective analysis relies on higher semantic features
- Examples:
  - A speed boat moving quickly in open water
  - A fishing boat moving slowly into the docks
  - A yacht circling slowly around landmark during night hours
- Motif representation



a sequence of **motifs**



with **motif attributes**

Motif-Oriented Feature Space

- Each motif expression has attributes (*e.g.*, speed, location, size, time)
- Attributes express how a motif was expressed
  - A right-turn at 30mph near landmark Y at 5:30pm
  - A straight-line at 120mph (!!!) in location X at 2:01am
- Motif-Oriented Feature Space
  - Naïve feature space
    1. Map each distinct motif-expression to a feature
    2. Trajectories become feature vectors in the new space
  - Let there be A attributes attached to every motif, each trajectory is a set of motif-attribute tuples

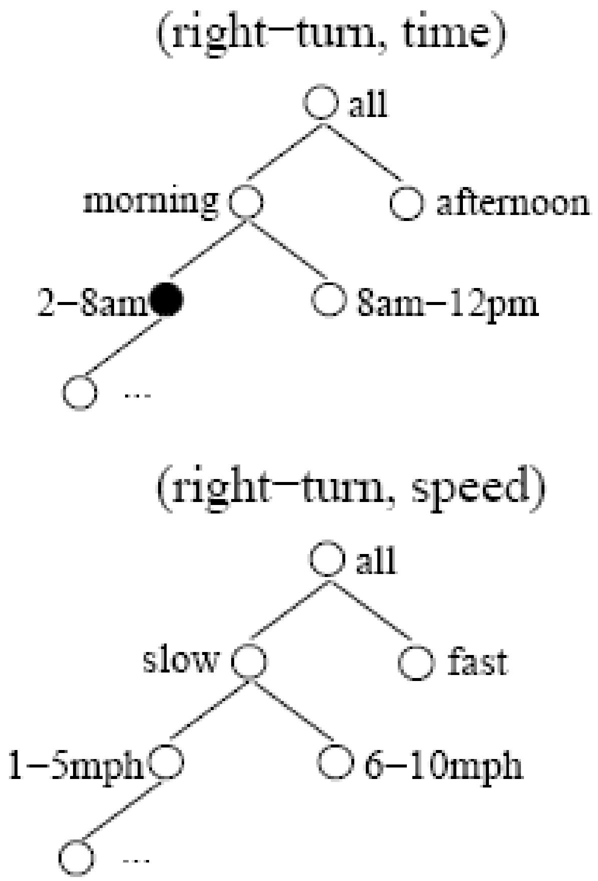
    $\{(m_i, v_1, v_2, \ldots, v_A), \ldots, (m_j, v_1, v_2, \ldots, v_A)\}$
  - Example:
    - Object 1: {(right-turn, 53mph, 3:43pm)} → (1, 0)
    - Object 2: {(right-turn, 50mph, 3:47pm)} → (0, 1)

Motif Feature Extraction

- Intuition: Should have features that describe general high-level concepts
  - "Early Morning" instead of 2:03am, 2:04am, ...
  - "Near Location X" instead of "50m west of Location X"
- Solution: Hierarchical micro-clustering
  - For each motif attribute, cluster values to form higher level concepts
  - Hierarchy allows flexibility in describing objects
    - e.g., "afternoon" vs. "early afternoon" and "late afternoon"

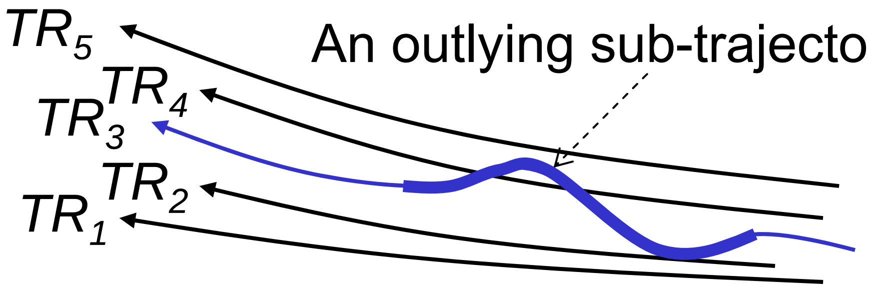
Feature Clustering

- Rough, fast micro-clustering method based on BIRCH (SIGMOD'96)
- Extracts a hierarchy for every motif-attribute combination
- Trajectories can be represented at arbitrary level of granularity



Trajectory Outlier Detection: A Partition-and-Detect Framework (Lee et al. 08)

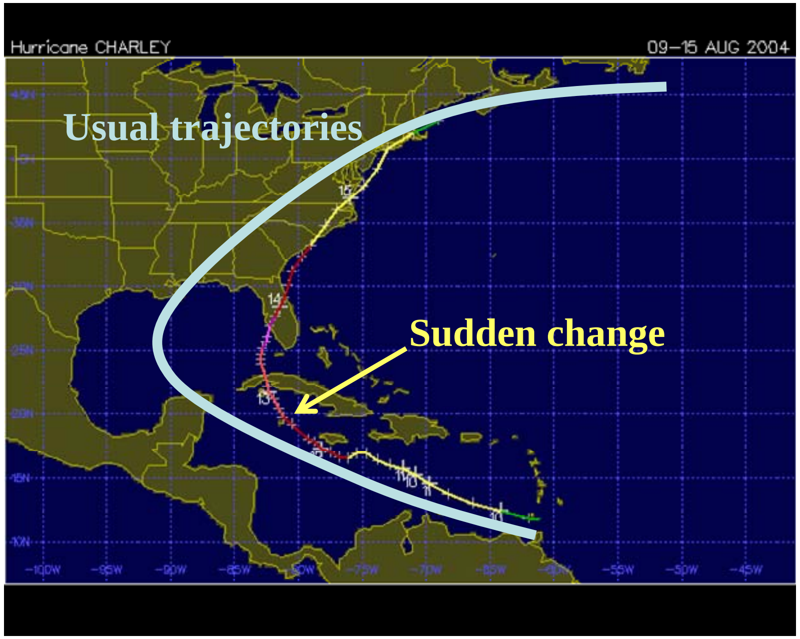
- Existing algorithms compare trajectories ***as a whole*** ➔ They might not be able to detect ***outlying portions*** of trajectories
  - e.g., TR_3 is not detected as an outlier since its overall behavior is similar to those of neighboring trajectories



- The ***partition-and-detect framework*** is proposed to detect outlying ***sub***-trajectories

Usefulness of Outlying *Sub*-Trajectories

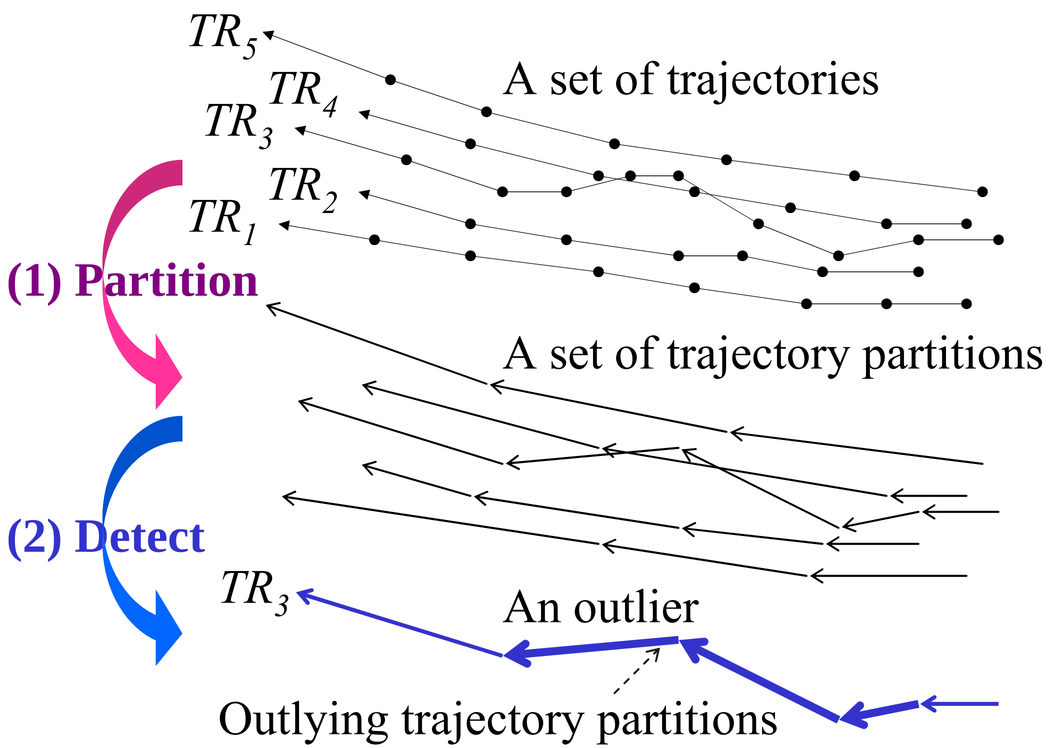
- Example: Sudden changes in hurricane's path



  - Since Hurricane Charley (Aug. 2004) was expected to hit the land closer to Tampa, many residents around Punta Gorda, Fla., were caught unprepared

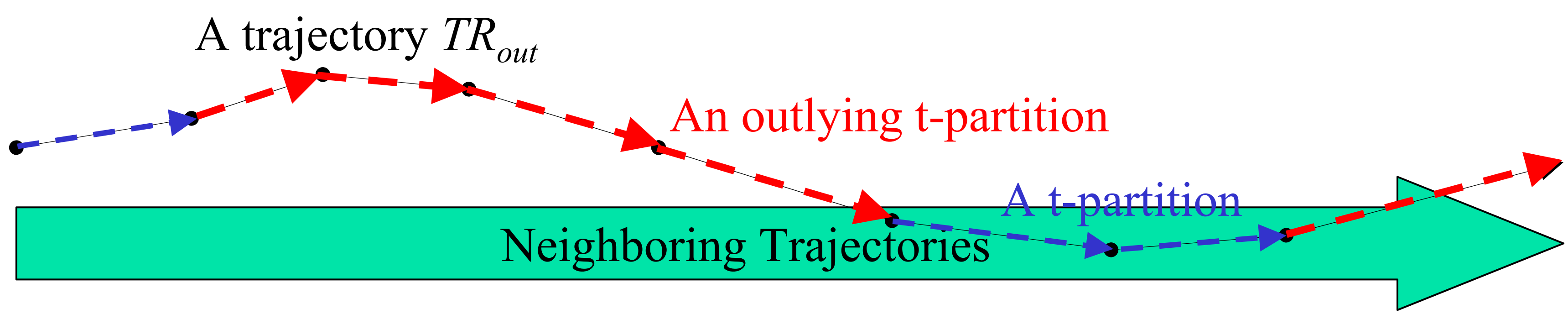
Overall Procedure

- Two phases: ***partitioning*** and ***detection***



Simple Trajectory Partitioning

- A trajectory is partitioned ***at a base unit***: the smallest meaningful unit of a trajectory in a given application
  - e.g., The base unit can be *every single point*



Pros: High detection quality in general

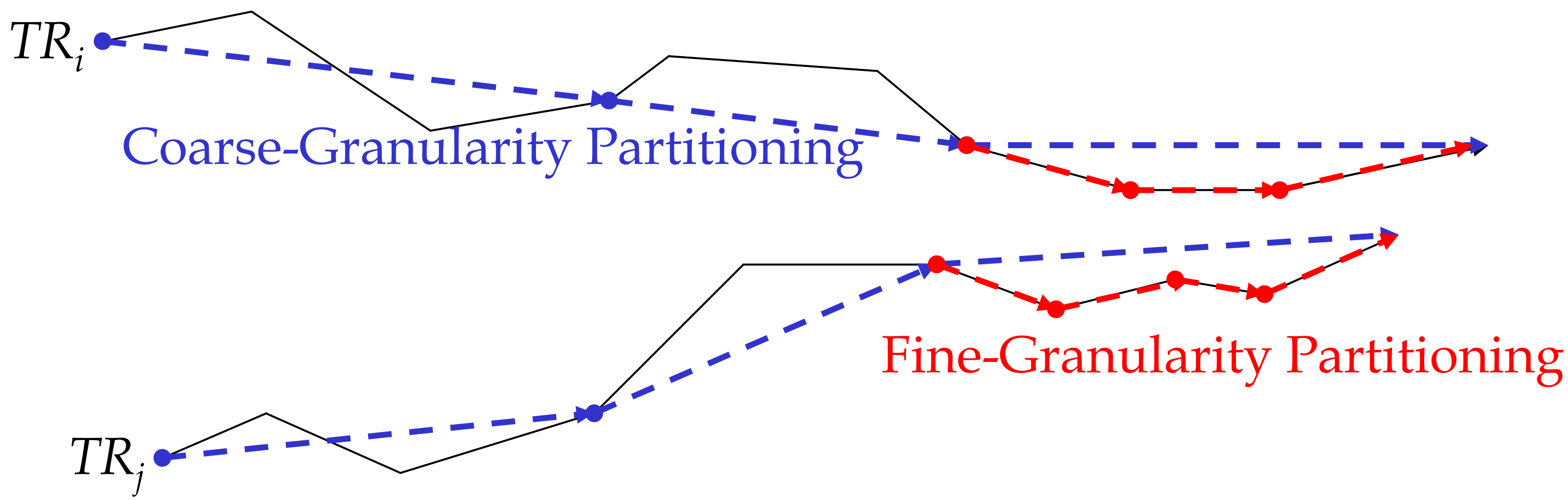
Cons: Poor performance due to a large number of t-partitions ➔ Propose a two-level partitioning strategy

Two-Level Trajectory Partitioning

- Objective
  - Achieves much higher performance than the simple strategy
  - Obtains the same result as that of the simple strategy; *i.e.*, does not lose the quality of the result
- Basic idea
  1. Partition a trajectory in *coarse granularity* first
  2. Partition a coarse t-partition in *fine granularity* ***only when necessary***
- Main benefit
  - Narrows the search space that needs to be inspected in fine granularity ⇒ Many portions of trajectories can be *pruned* early on

Intuition of Two-Level Trajectory Partitioning

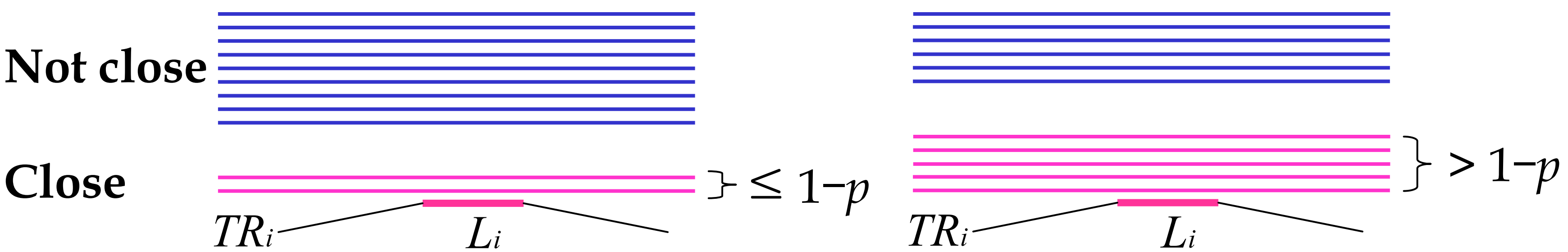
- If the distance between coarse t-partitions is very large (or small), the distances between their fine t-partitions are also very large (or small)



- The lower and upper bounds for fine t-partitions are derived in the paper

Outlier Detection

- Once trajectories are partitioned, trajectory outliers are detected based on both *distance* and *density*
- An *outlying t-partition* is defined as

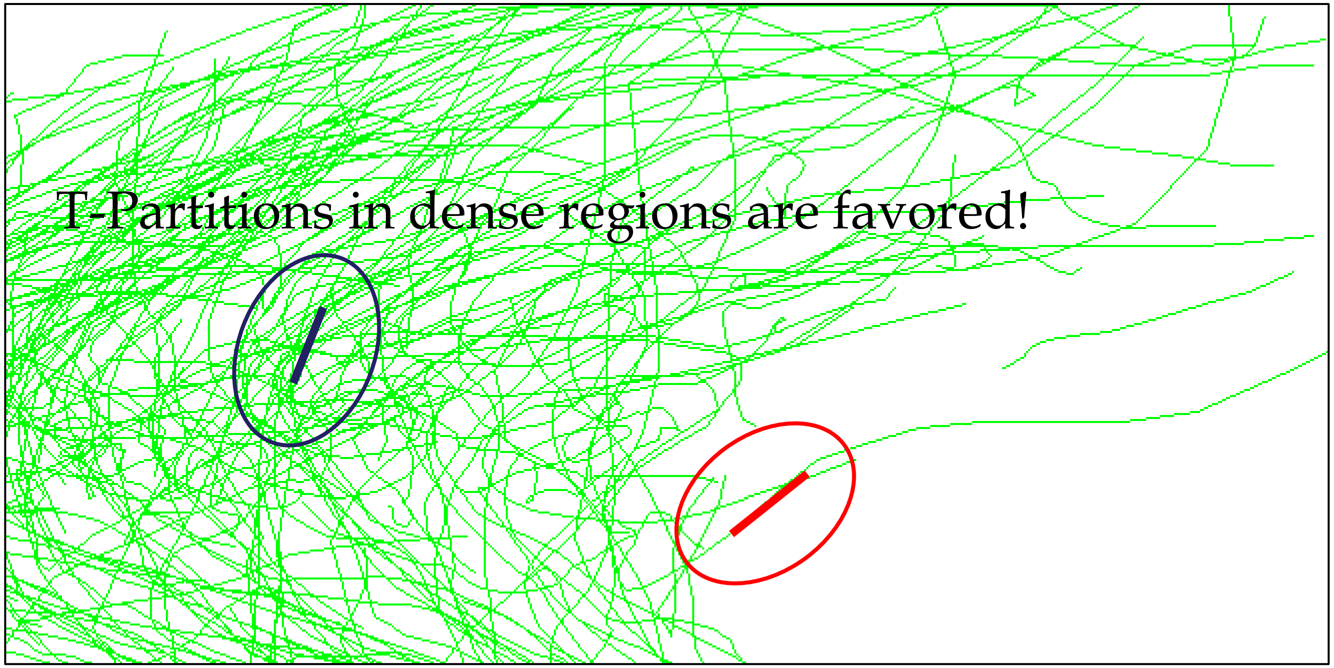


L_i is an *outlying t-partition* L_i is not an outlying t-partition

- A trajectory is an *outlier* if it contains a sufficient amount of outlying t-partitions

Incorporation of Density

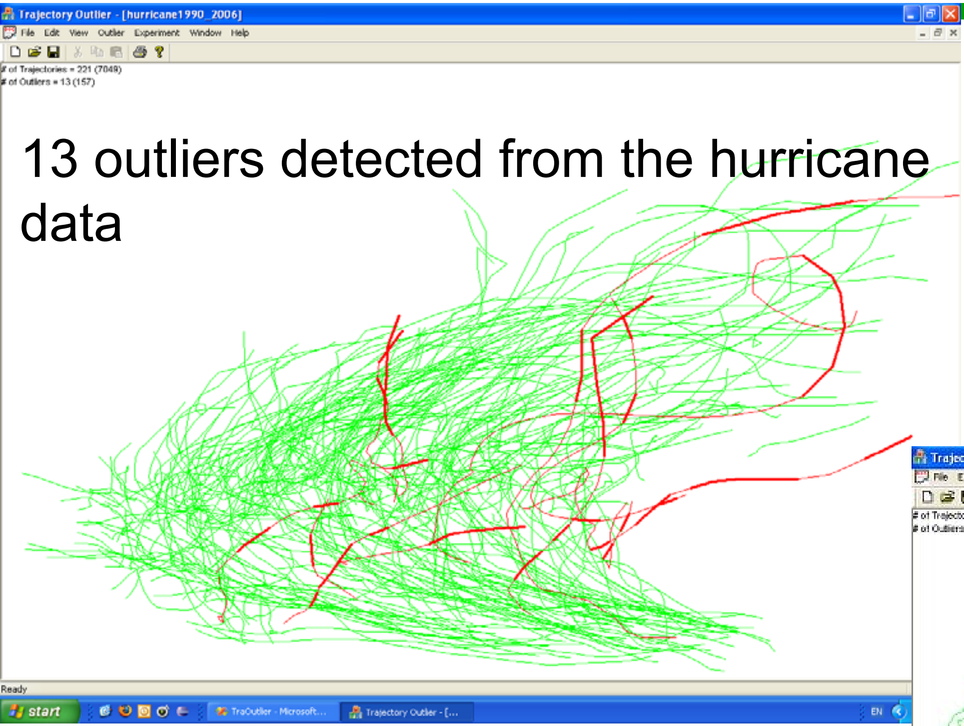
- The number of close trajectories is adjusted by the density of a t-partition



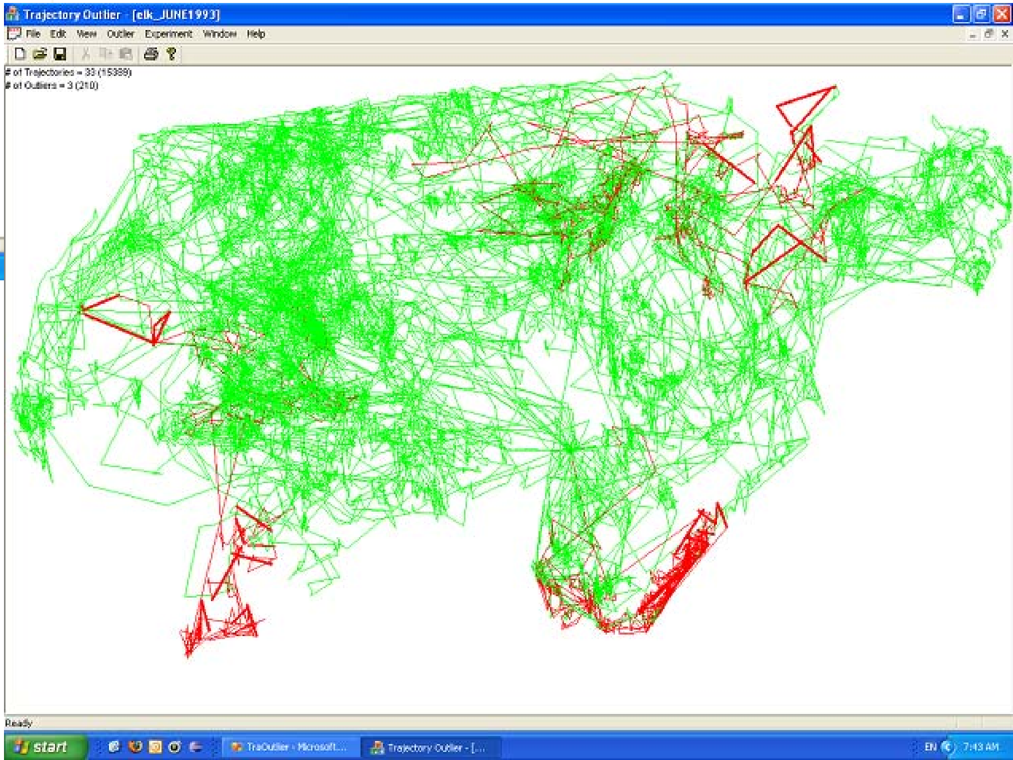
- Dense region ➔ Decreased, Sparse region ➔ Increased

Experiments: Sample Detection Results

13 outliers detected from the hurricane data



Three outliers found from the Elk Data



Summary: Moving Object Mining

- Pattern Mining
  - Trajectory patterns, flock and leadership patterns, periodic patterns,
- Clustering
  - Probabilistic method, density-based method, partition-and-group framework
- Prediction
  - linear/non-linear model, vector-based method, pattern-based method
- Classification
  - Machine learning-based method, HMM-based method, *TraClass* using collaborative clustering
- Outlier Detection
  - Unsupervised method, supervised method, partition-and-detect framework

Tutorial Outline

- Part I. Mining Moving Objects
- Part II. Mining Traffic Data
- Part III. Conclusions

Part II. Traffic Data Mining

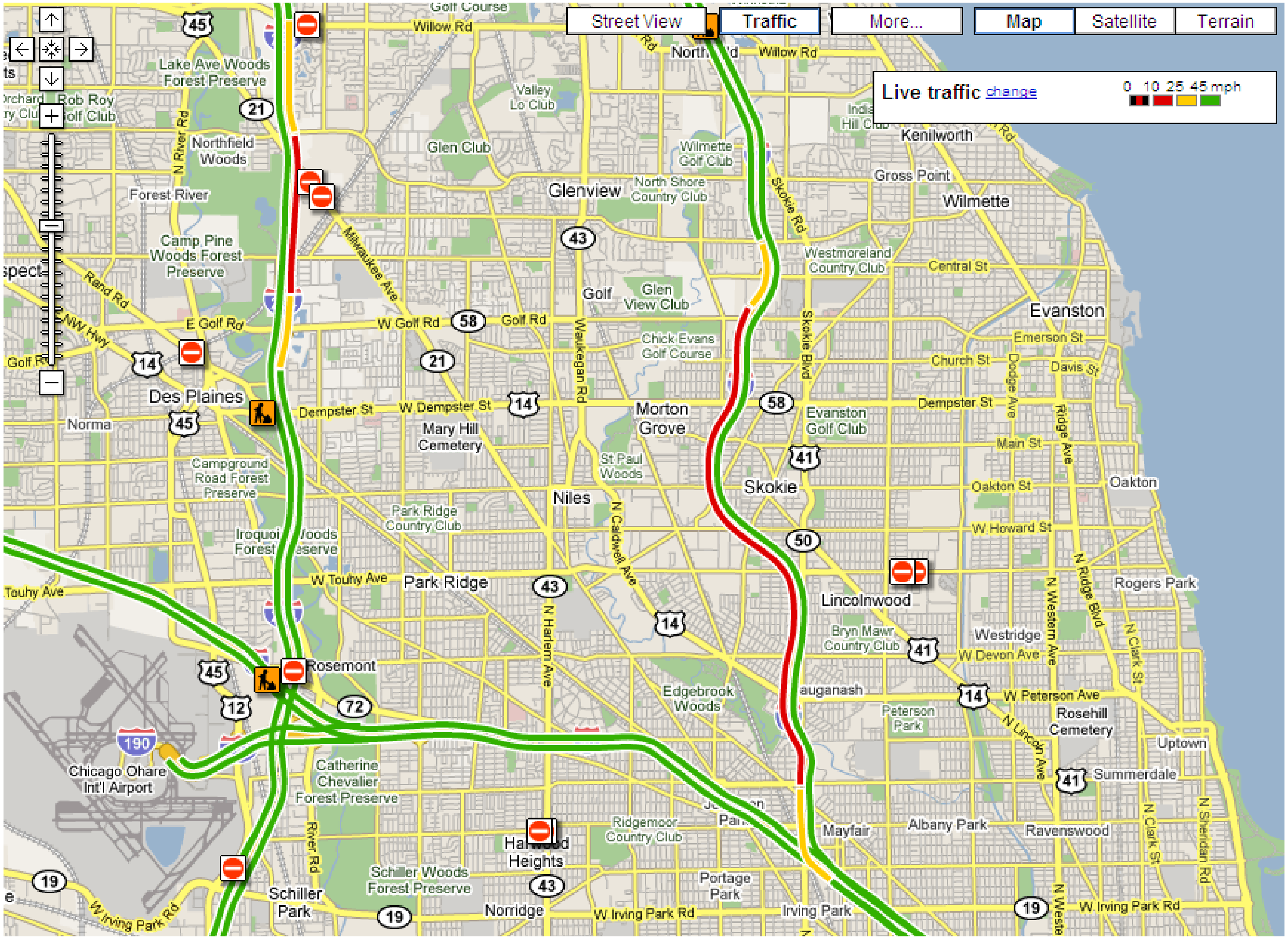
- Introduction to Traffic Data
- Traffic Data Warehousing
- Route Discovery by Frequent Path Pattern Analysis

Trillion Miles of Travel

- MapQuest
  - 10 billion routes computed by 2006
- GPS devices
  - 18 million sold in 2006
  - 88 million by 2010
- Lots of driving
  - 2.7 trillion miles of travel (US – 1999)
  - 4 million miles of roads
  - $70 billion cost of congestion, 5.7 billion gallons of wasted gas

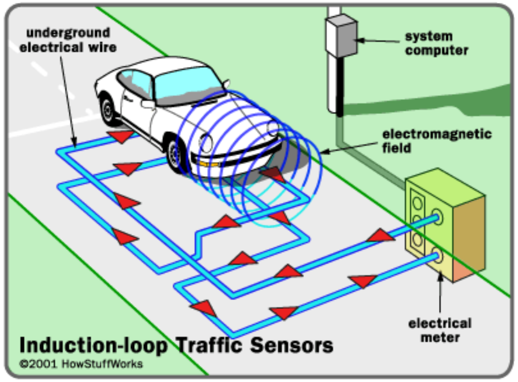
Abundant Traffic Data

- Google Maps provides live traffic information



Traffic Data Gathering

- Inductive loop detectors
  - Thousands, placed every few miles in highways
  - Only aggregate data
- Cameras
  - License plate detection
- RFID
  - Toll booth transponders
  - 511.org – readers in CA



Road Networks

Speed Pattern:
65 mph non rush
35 mph rush hour

Node: Road intersections

Edge: Road segment

Driving Pattern: Preferred Routes

Part II. Traffic Data Mining

- Introduction to Traffic Data
- Traffic Data Warehousing
- Route Discovery by Frequent Path Pattern Analysis

Traffic Cube: Motivation Examples

- Ex. 1. Bob is a bagpack traveler and he is new to Los Angles. He wants to know
  - Where are the places the traffic jams are most likely to happen in weekend?
  - When is the best time to visit the Hollywood to avoid heavy traffic?
- Ex. 2. Jim is the head of the transportation department in Los Angeles, the department recently got limited funds to improve roads
  - On which highway the traffic is usually heavy during the morning rush hours?

Problem of Traditional Query

- **Select** highway name **from** traffic table **where** speed < 40 mph and Region is Los Angeles

  #101, segment id 2, 36 mph, 3:50 pm

  #10, segment id 5, 33 mph, 3:50 pm

  # 101, segment id 3, 34 mph, 4:00 pm

  - The results are not organized
  - Too trivial
- Google Traffic is good to visualize current traffic, it also provides prediction function, but no analysis on historical data

User Requirements

- Users demand summaries in their interested time, region, scale, etc.
  - Bob is only interested in Hollywood region on weekend
  - Jim is more concerned on the whole Los Angeles on weekdays
- Users are more interested in the information related to traffic jams, incidents, slow traffic—the congestions

Features of Traffic Data

- Huge Size
  - Thousands of road sensors, reporting the data in a time frequency of 30 seconds
  - The traffic databases contains Giga-bytes, even Tera-bytes of data
  - Most of them are normal records (the speed reading is close to the speed limit of the road)
  - Congestions are dwarfed by normal data
- Complex Object
  - A congestion is a complex object with several road segments and varied time length – hard to model

Traffic Monitoring Systems

- PeMS: collects data in California highway
- CarWeb: collects real time GPS data from cars
- Google Traffic: Toolkit on Google Map
- CubeView by Shekhar et al: Implement traditional OLAP on the traffic data
- AITVS: based on CubeView, using two more distinct views to support investigation
- Most focus on **SQL based queries**, lacking analysis power
- Build on the whole dataset – **huge I/O** overhead, atypical data are dwarfed

Spatial/Traffic/Trajectory Data Cubes

- Spatial Cube (Stefanovic et al. 2000)
  - Dimension members are spatially referenced and can be represented on a Map
- Trajectory Cube (Giannotti et al. 2007)
  - include temporal, spatial, demo-graphic and techno-graphic dimensions, two kinds of measures: spatial measure and numerical measure
- Flow Cube (Gonzalez et al. 2007)
  - Analyzing item flows in RFID applications
- Congestion Cube: On-going work
  - Multidimensional analysis of traffic congestions

Congestion Event

- A congestion is a dynamic process:
  - start from a single segment of the streets
  - expand along the road and influence nearby roads
  - may cover hundred road segments when reaching the full size
  - As time passes by, those fragments shrink slowly and eventually disappear.
- Group the congestion records that are spatially close and timely relevant to be a congestion event

Base Congestion Cluster

- For each road segment in the congestion event, record the seg_id, total_duration and avg_speed
- Congestion Event:
  - Seg_1, 9:00 am, 30 mph
  - Seg_2, 9:00 am, 35 mph
  - Seg_1, 9:05 am, 40 mph
  - …
- Base Congestion Cluster
  - Seg_1, 30 mins, 32.5 mph
  - Seg_2, 20 mins, 35 mph

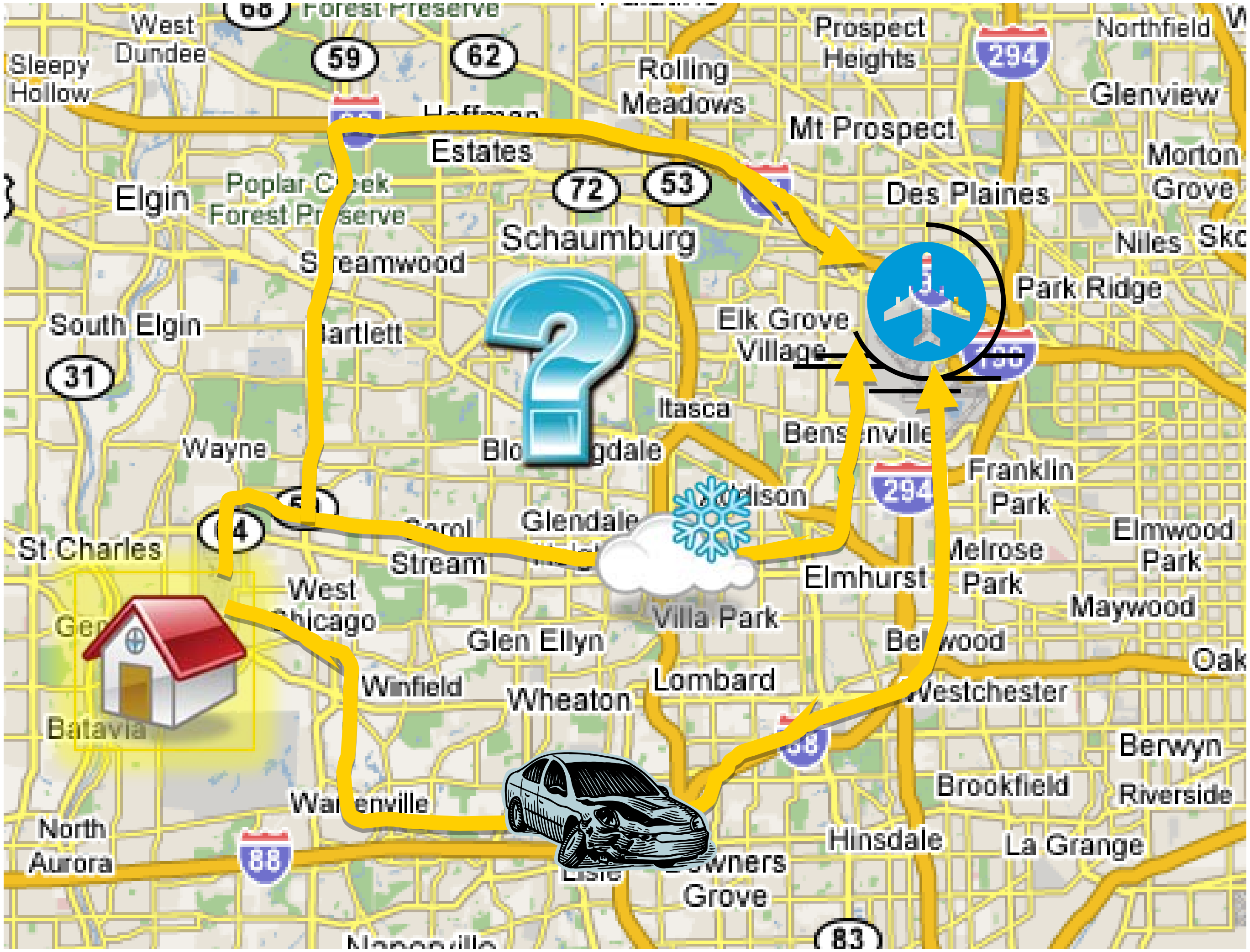
Congestion Cluster and Congestion Cube

- Natural and distinguishable
- Congestion cube: Constructed based on congestion clusters

Part II. Traffic Data Mining

- Introduction to Traffic Data
- Traffic Data Warehousing
- Route Discovery by Frequent Path Pattern Analysis

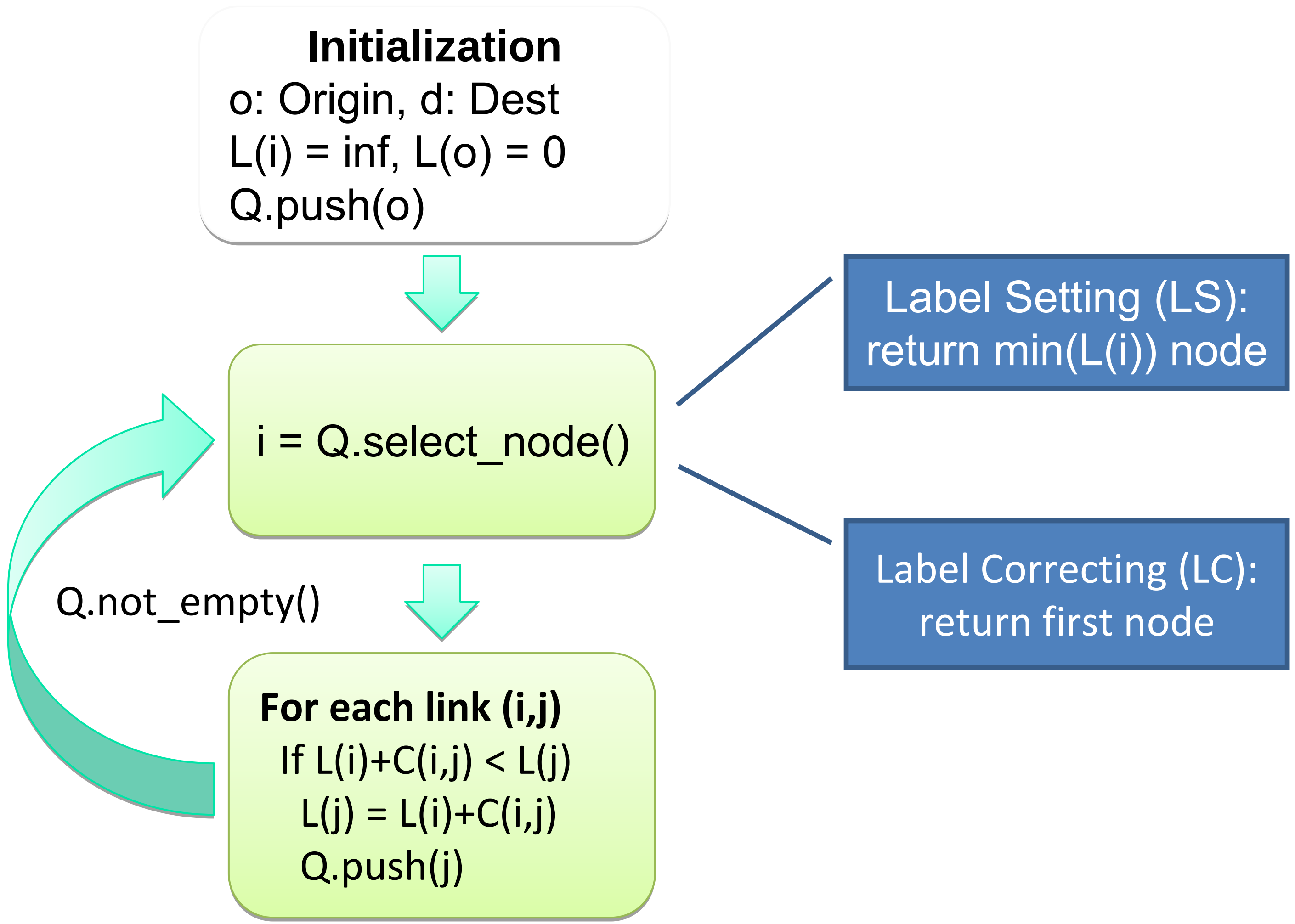
Route Planning



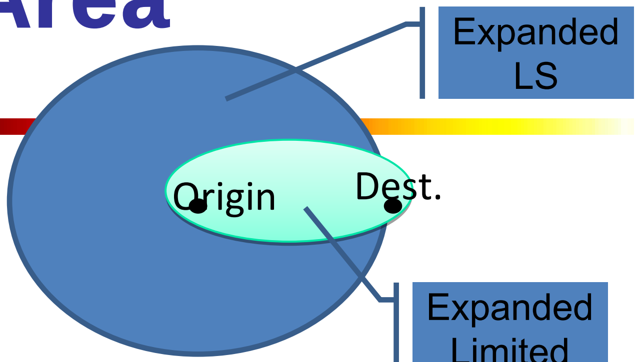
Heuristic Shortest Path Algorithms for Transportation Networks (Fu et al.'06)

- Problem
  - Route Guidance System (RGS)
  - Route Planning System (RPS)
  - Second level response, queries on large networks
- Solution: Heuristic search
  1. Limit Search Area
  2. Search Decomposition
  3. Limit Examined Links

General Algorithm

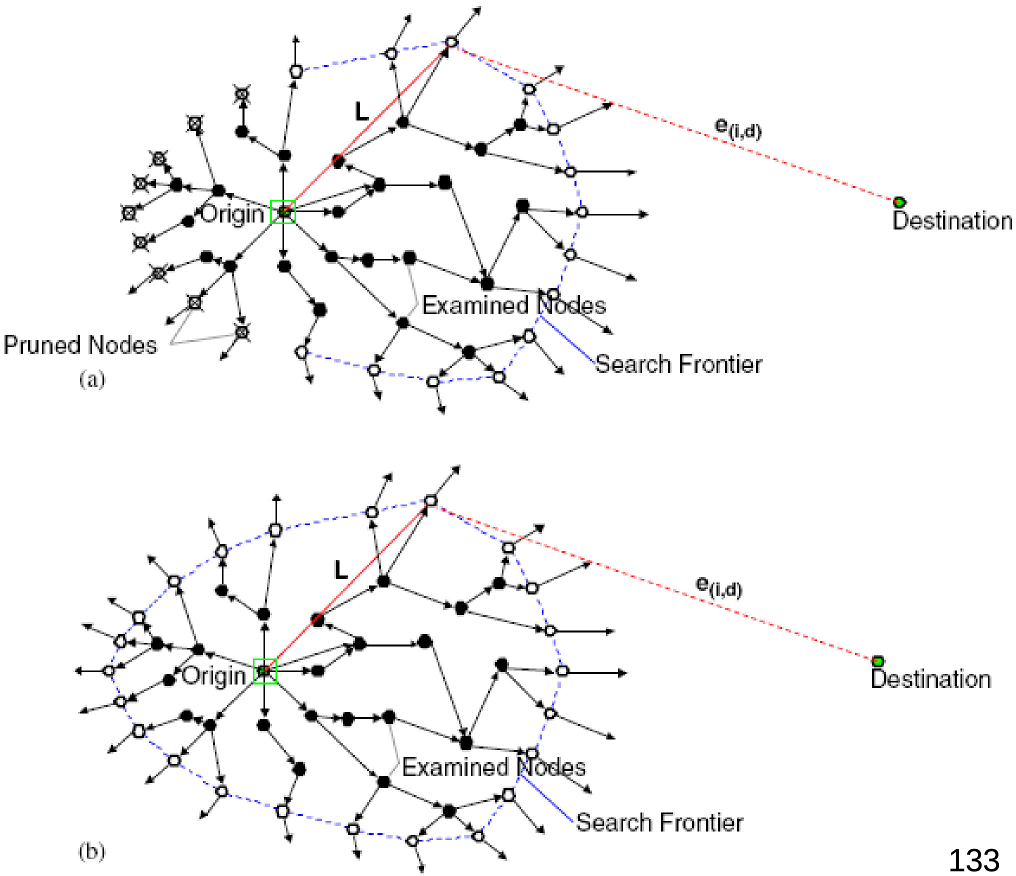


Method 1. Limit Search Area



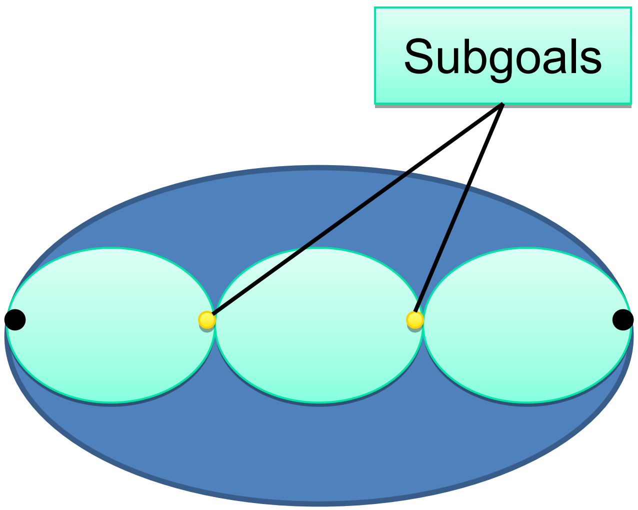
- Branch Pruning [Fu et al. 96, Karim 96]

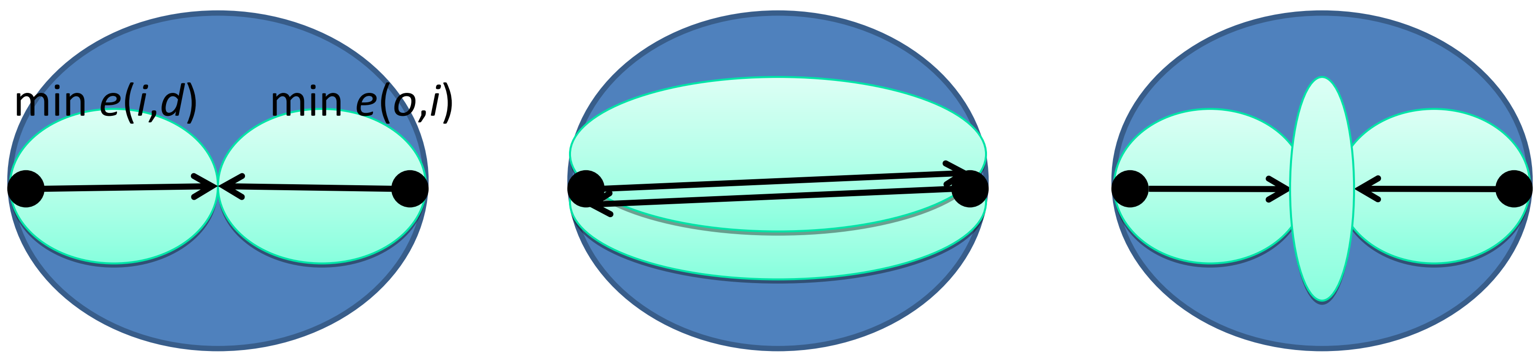
  Q.select_node()
  - Select node if $L(i) + e(i,d) < E(o,d)$
  - Prune unpromising nodes
  - Expands: 20% of LS
- A-Star [Hart 68, Nilsson 71]
  - Select node with min $L(i) + e(i,d)$
  - Prioritize promising nodes
  - Expands: 10% of LS
- Branch Pruning vs. A-Star



Method 2. Search Decomposition

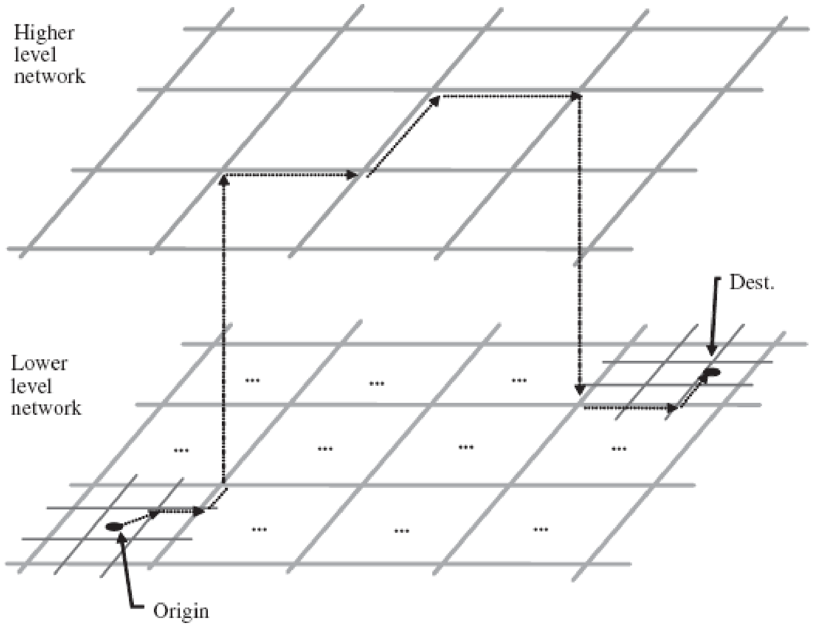
- Algorithm cost grows faster than graph size
- Decompose problem
  - Subgoals
    - [Bander et al. 91]
    - [Dillenburg et al. 95]
  - Bidirectional Search
    - [Dantzig 60, Nicholson 66]





Method 3. Limit Links: Hierarchical Search

- Divide a graph into layers
  - Top Layer:
    - Small
    - Large roads
  - Bottom Layer:
    - Large
    - Contains all roads



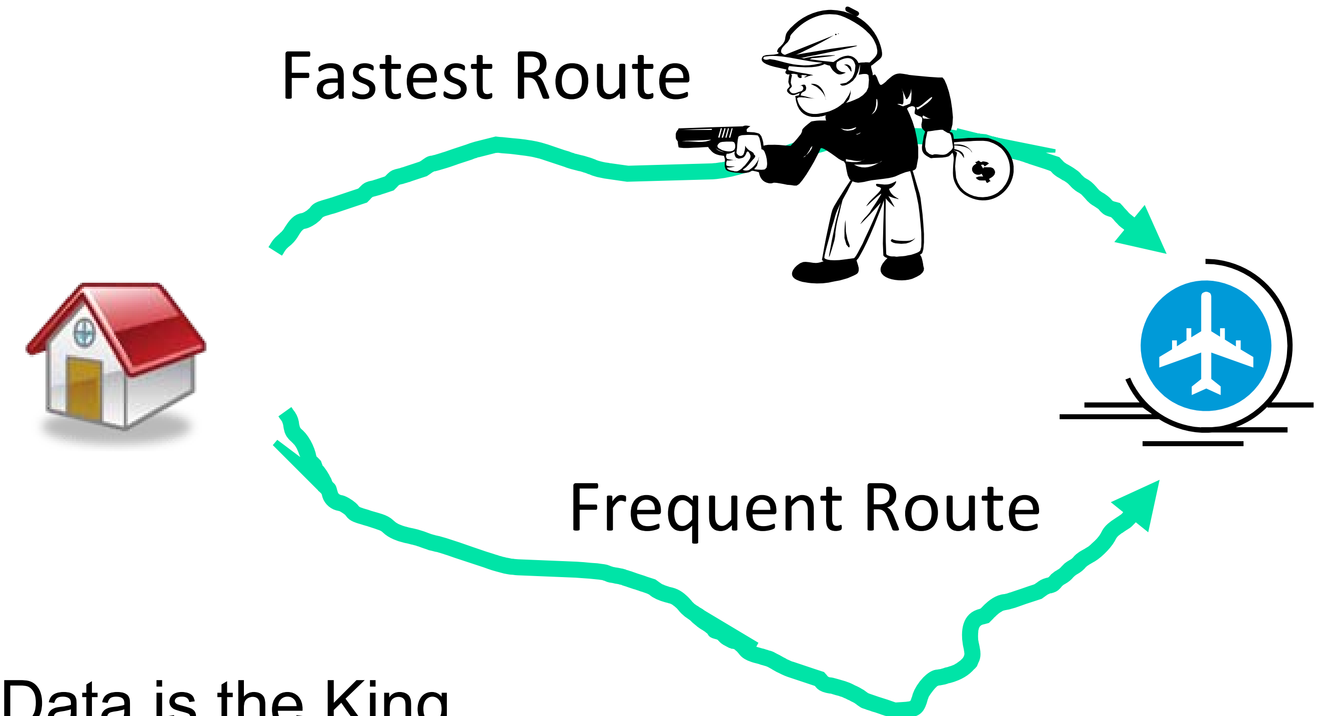
- Strategy
  - Search an entry point to top layer
  - Run the standard A-Star on top layer
- Orders of magnitude faster than A-star
- References: [Polya'45, Sacerdoti'74, Korf'87, Timpf et al. '92, Car et al.'94, Liu'97, Chou et al.'98, Jagadish et al.'02, Jung et al.'02]

Hierarchical Search

- Speedup
  - Linear in search space
  - Orders of magnitude faster than A-Star
  - Only viable option
- Sub-optimal solution
  - Path 9% - 50% slower than optimal
  - No shortcuts between top/bottom layers
  - Bad for short trips
    - Better to avoid highways

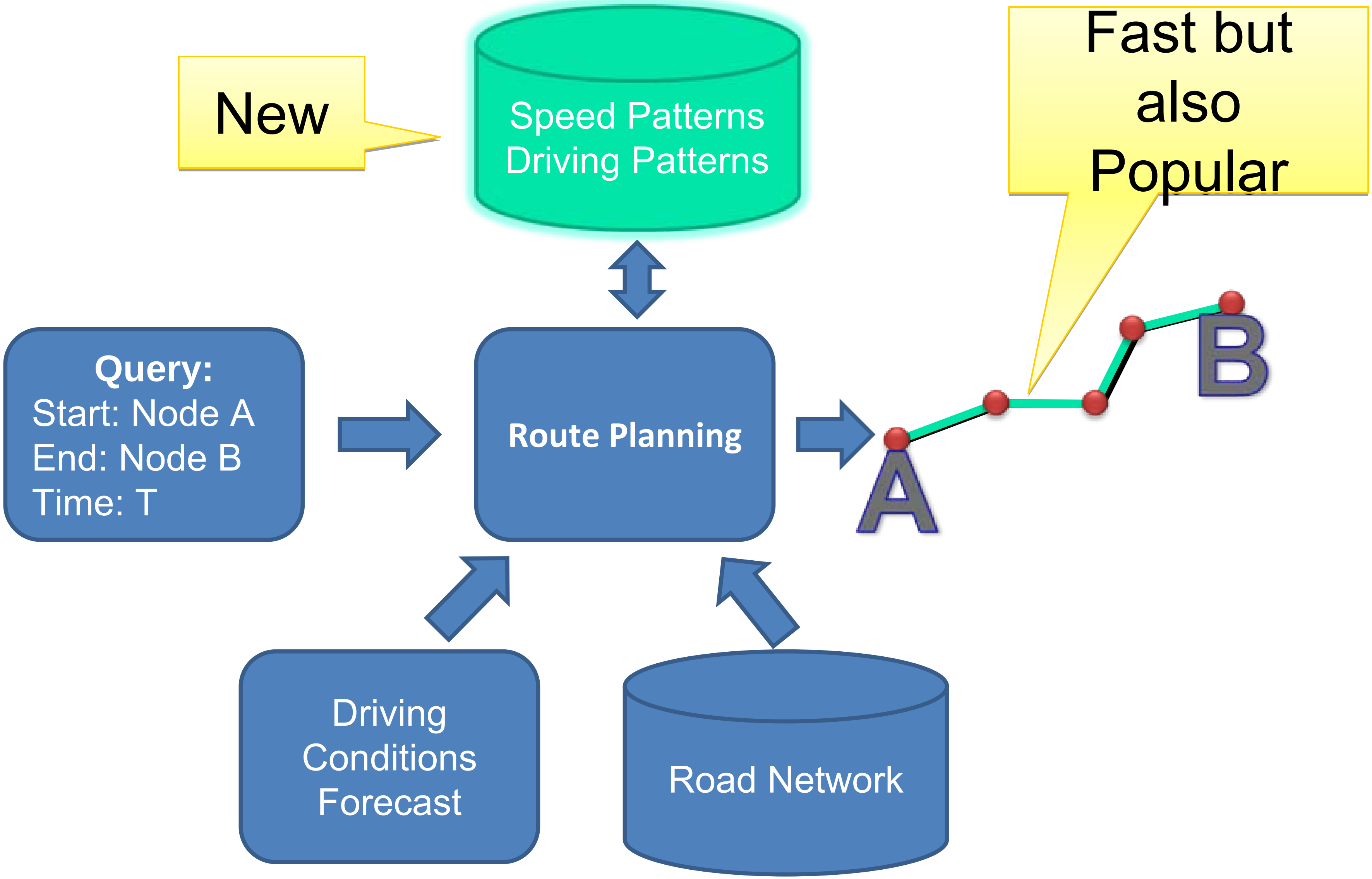
Mining Frequent Routes: When in Rome, Do as the Romans Do

Adaptive Fastest Path Computation on a Road Network [Hector et al. 07]



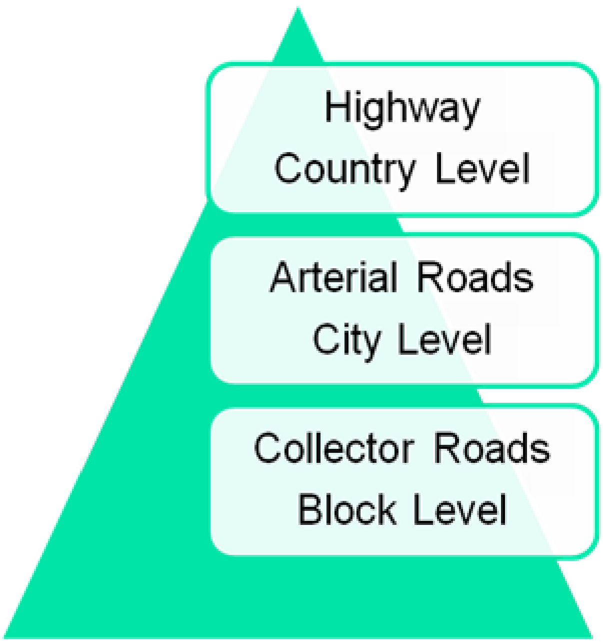
- Data is the King
- No model can anticipate all variables

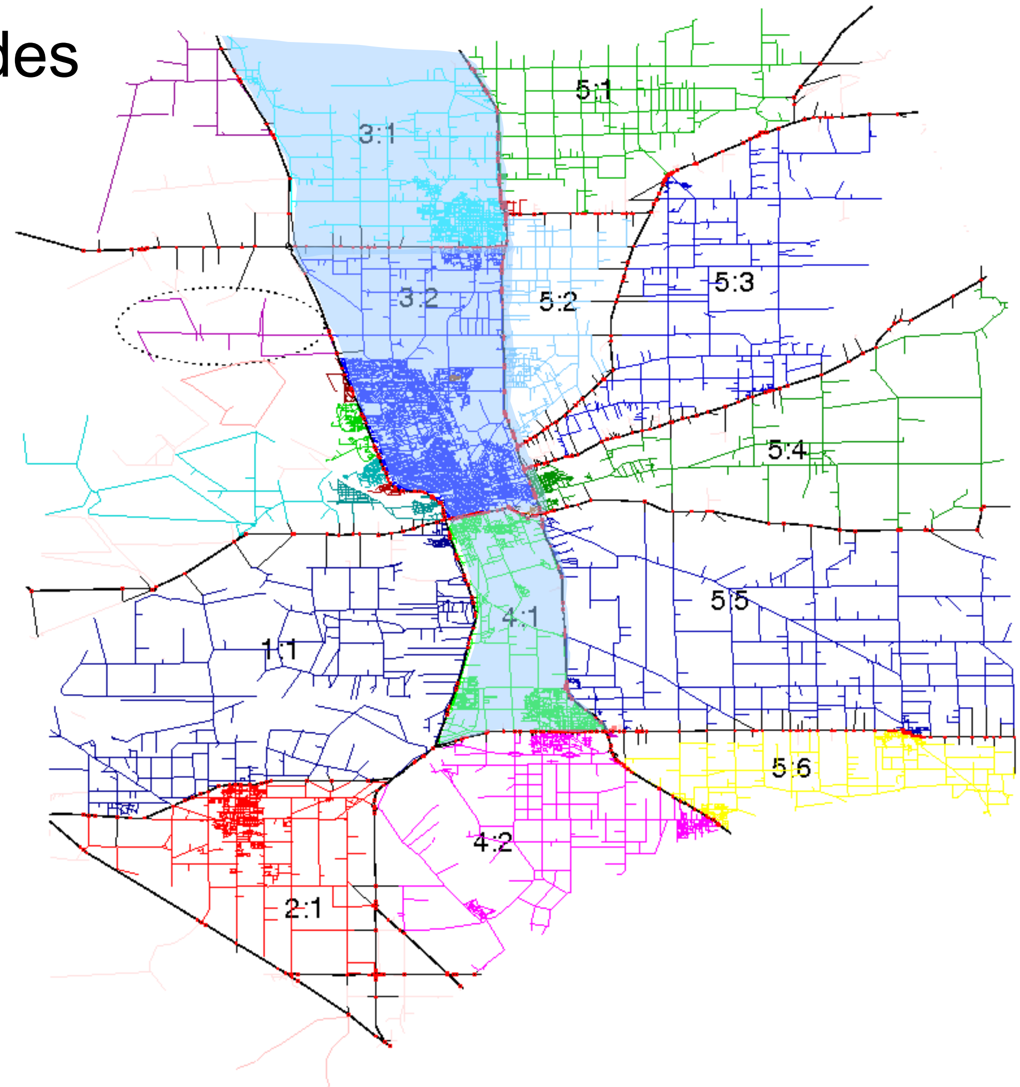
Mining for Fast and Popular Routes



Road Network Partitioning

- Road hierarchy provides natural partition





Traffic Data

car_id	eid	Time	Speed	Conditions
1	1	10	30	rain, no construction, accident
1	2	12	25	rain, no construction, no accident
2	10	11	60	good weather, no construction, accident
...	...		...	...

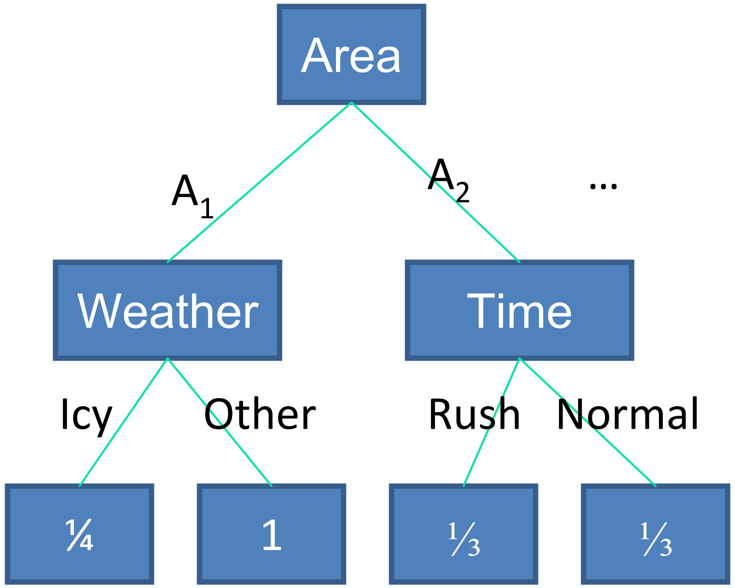
RFID: Yes
Loop Sensor: No

Computed Successive Observations

National Weather Service
Transportation Management Centers

Mining Speed Patterns

- Model of speed changes
- Classification
  - Given conditions predict speed (discrete)
  - We use decision tree
- Regression problem
  - Given conditions predict speed (continuous)



Mining Driving Patterns

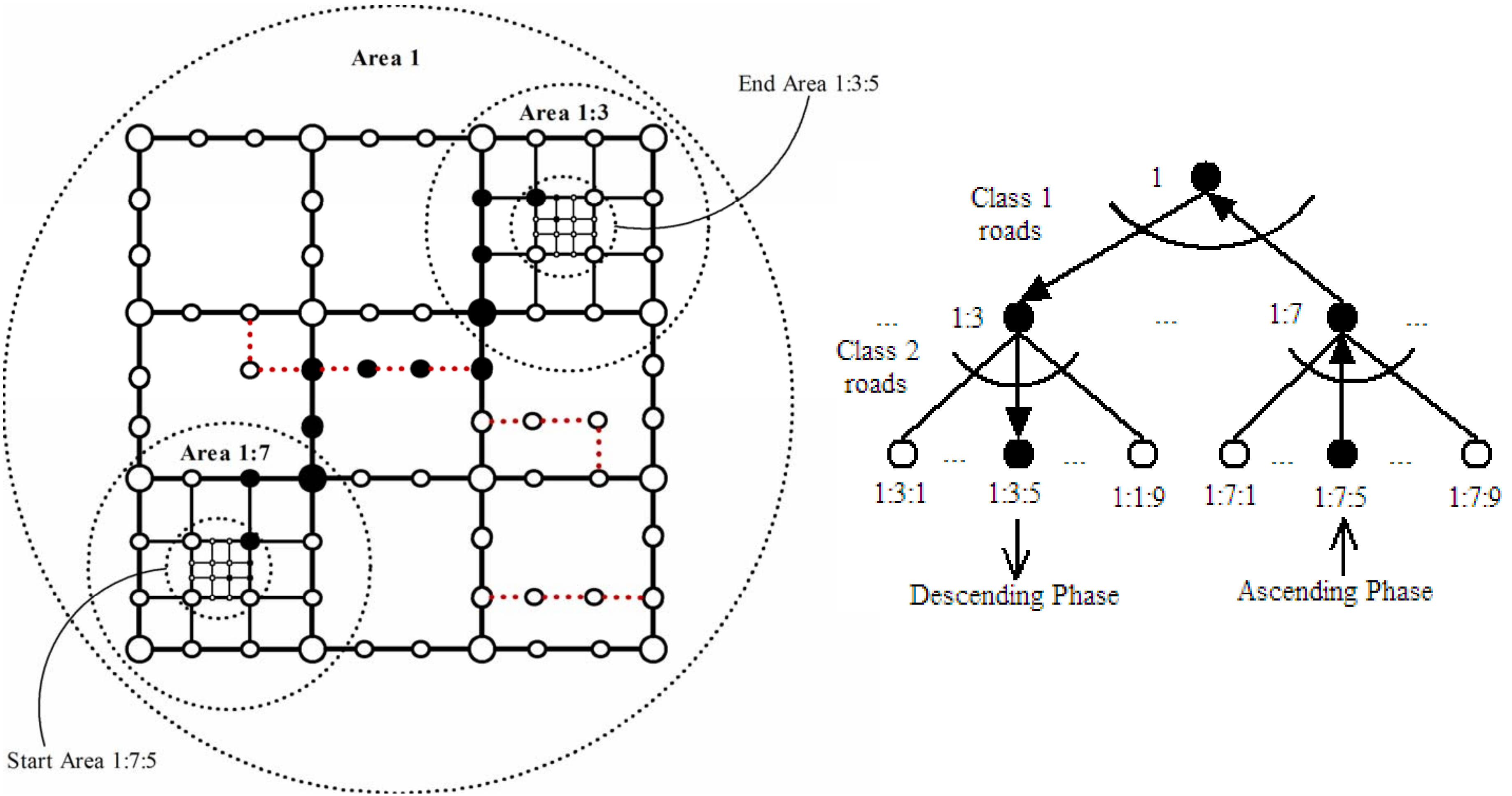
- For each area:
  - Define minimum support
  - Mine frequent trajectories
    - Length *k*: For RFID Data
    - Length 1: For loop detectors

Driving Conditions	Area	Popular Routes
All	A_1	{r1,r3,r5}
Snow	A_2	{r13,r29}
Rush Hour, Any Weather	A_3	{r6,r6}

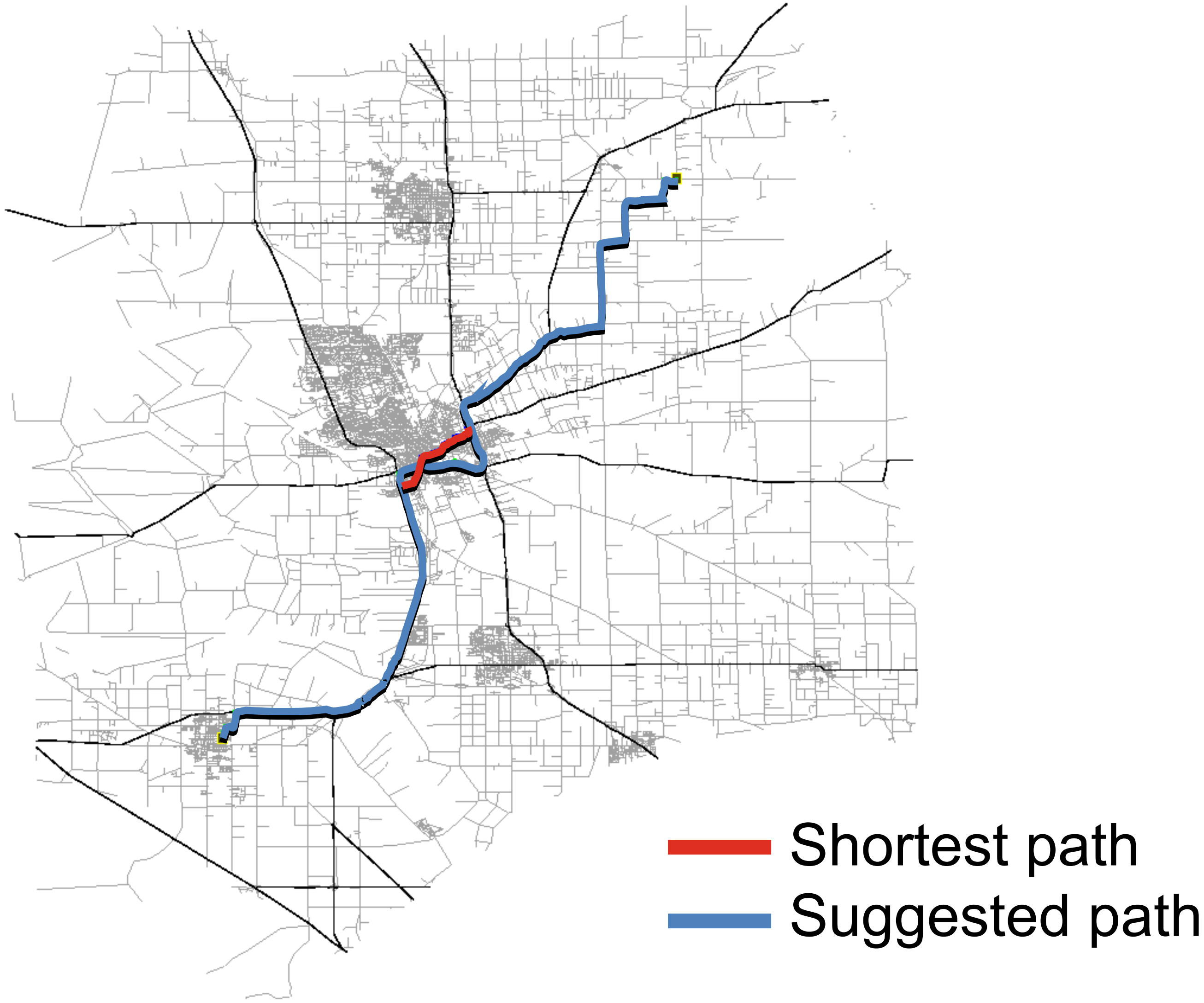
Hierarchical Route Planning

- Ascending Phase
  - Move from start through successively bigger roads towards goal
- Move only through large roads
- Descending Phase
  - Move towards goal through successively smaller roads
- At each step
  - Select frequently traveled roads
  - Use dynamic speed model

Example: Hierarchical Route Planning



Result: San Joaquin Route



Summary: Traffic Data Mining

- Traffic Warehousing
  - Congestion cluster based approach
  - Heuristic methods to mine significant clusters
- Route Discovery
  - Heuristic methods (Limit Search Area, Search Decomposition, Limit Examined Links), adaptive method
- Hot-Route Detection
  - FlowScan

Tutorial Outline

- Part I. Mining Moving Objects
- Part II. Mining Traffic Data
- Part III. Conclusions

Conclusions

- Mining moving object data, trajectory data and traffic data are important tasks in data mining
  - Lots of rich and exciting results
- This tutorial has presented an overview of recent approaches in this direction
- Promising research directions
  - Moving object/traffic mining in cyber-physical networks
  - Integration with heterogeneous information networks
  - Exploration of diverse applications

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