Georgia Tech College of Computing
Defining the New Face of Computing

DISL

Trajectory Clustering

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Introduction

- Pervasive use of GPS/Wifi-enabled devices
  - 295 million smartphones in 2010 to 1.2 billion units in 2015
- Explosion of location-based apps and services
  - LBS global revenue is from $2.8 billion in 2010 to $10.3 billion in 2015 [add citation]
- Huge amount of Location Data generated from multiple sources
  - GPS, WiFi, Social networks, RFID and senors




From Location Tracking to Location Analytics

- Increased interests and demand for deriving values and hidden insights from huge and growing location data
- Location Analytics (What):
  - Inference and knowledge discovery from mining location data of all types
- Opportunities
  - understanding how human mobility impacts the evolution of economy, transportation, healthcare and many aspects of the society we live and the infrastructure around us
- Broad LBS and apps:
  - Traffic management
  - Urban planning
  - Geo-marketing
  - Mobile adversting
  - Location-based recommendation systems

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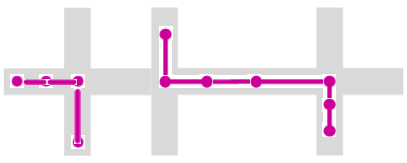
Three Types of Location Data

- Point based location data
  - Geometric position points from GPSs & sensors
- Area based location data
  - Symbolic address
  - A geometry area such as rectangle produced by WiFi localization, finger-print based localization, etc.

•Location analysis algorithms are cent ered on querying and mining point-based or area-based positions.

- Trajectory based location data
  - Mobile object trajectories, each consists of a timer series of position points, representing a travel path of a moving object



•Architectures & algorithms for analyzing and mining trajectories of mobile objects .

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Trajectory Mining: Technical Challenges

- MO trajectories have complex characteristics
  - Temporal sequences of spatial location points
  - Varying-sample size sequences represent mobile objects' movement paths of varying lengths
    - Geometric points are unique and may contain outliers due to errors in location sensing and location acquisition
  - Moving object trajectories are typically constrained by the physical road network
- Large-scale trajectory analysis
  - High efficiency and high accuracy
  - Online/offline trajectory data processing and mining

Traditional mining algorithms fail to perform effectively on mobile object trajectory data

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Research Hypothesis

- Trajectory mining should consider the physical paths of moving objects
  - road networks, walking paths
- Trajectory mining should take into account the motion behaviors and preserve the temporal sequence of trajectories.
- Trajectory mining should effectively handle varying length trajectories while minimizing any bias.
- Trajectory mining should consider semantic locations covered by mobile object trajectories
- Trajectory mining should efficiently target at both speed and quality, scalable in terms of volume, different types and sizes of trajectory data

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Three Categories of Trajectory Mining Research

- Clustering location points of Trajectories
  - finding where in Atlanta is most crowded on Friday night
- Clustering whole trajectories
  - finding the traffic patterns in a city
- Clustering subtrajectories
  - finding the most frequently traveled road segments

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Clustering

- Definition: the process of grouping a set of physical or abstract objects into classes of *similar* objects [11]
- Applications: market research, pattern recognition, data analysis, image processing, etc.
- Representative algorithms: *k*-means [17], BIRCH [24], DBSCAN [6], OPTICS [2], and STING [22]
- Target data: previous research has mainly dealt with clustering of *point* data

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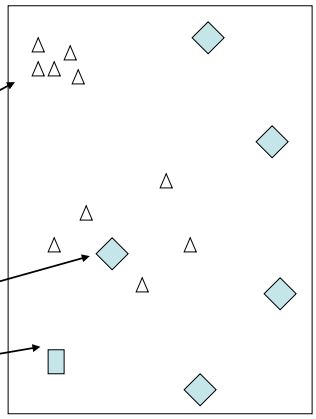
Hot spots

- Question addressed
  - Is a phenomenon spatially clustered?
  - Which spatial entities or clusters are unusual?
  - Which spatial entities share common characteristics?
- Examples:
  - Cancer clusters [CDC] to launch investigations
  - Crime hot spots to plan police patrols
- Defining unusual
  - Comparison group:
    - neighborhood
    - entire population
  - Significance: probability of being unusual is high



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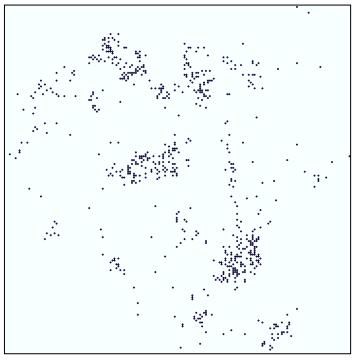
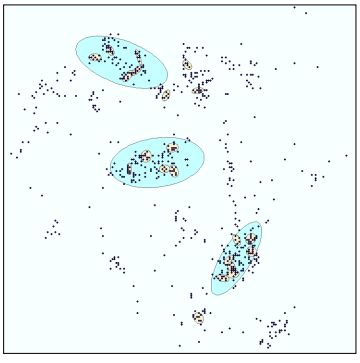
Spatial data exploration

- Hot spot analysis – Hierarchical NN

Cancer incidence data 1st and 2nd order clusters





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- www.spatialanalysisonline.com
- 3rd edition

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Algorithmic Ideas in Clustering

- Hierarchical –
  - All points in one clusters
  - then splits and merges till a stopping criterion is reached
- Partitional –
  - Start with random central points
  - assign points to nearest central point
  - update the central points
  - Approach with statistical rigor
- Density
  - Find clusters based on density of regions
- Grid-based –
  - Quantize the clustering space into finite number of cells
  - use thresholding to pick high density cells
  - merge neighboring cells to form clusters

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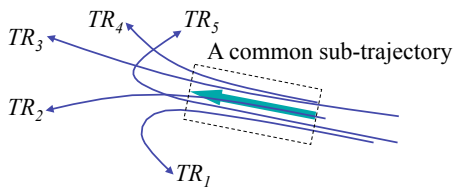
Limitations of Existing Algorithms

- The position based clustering cannot provide insight on trajectories and trajectory patterns.
- The while trajectory clustering algorithm (such as those proposed by Gaffney et al. [7, 8]) clusters trajectories *as a whole.*
  - Clustering trajectories as a whole could not detect *similar portions* of the trajectories (i.e., common *sub*-trajectories)
  - **Example**: if we cluster TR_1~TR_5 as a whole, we cannot discover the common behavior since they move to totally different directions



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Discovery of Common *Sub*-Trajectories

- Discovering common ***sub***-trajectories is very useful, especially if we have regions of special interest
  1) *Hurricane Landfall Forecasts* [18]
     Meteorologists will be interested in the common behaviors of hurricanes *near the coastline* or *at sea* (i.e., before landing)
  2) *Effects of Roads and Traffic on Animal Movements* [23]
     Zoologists will be interested in the common behaviors of animals *near the road* where the traffic rate has been varied
- Subtrajectory clustering solution is to partition a trajectory into a set of line segments and then group similar line segments
  ⇒ A ***partition-and-group*** framework
  ⇒ NEAT, a road network aware subtrajectory clustering framework

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SIGMOD 2007

Trajectory Clustering: A Partition-and-Group Framework

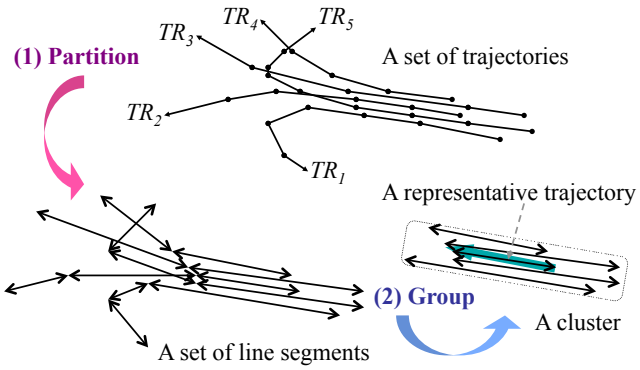
June 13, 2007

Jae-Gil Lee[1)], **Jiawei Han**[1)], **and Kyu-Young Whang**[2)]

[1)] Dept. of Computer Science, UIUC, USA
[2)] Dept. of Computer Science, KAIST, Korea

The *Partition-and-Group* Framework

- Consists of two phases: *partitioning* and *grouping*



Note: a representative trajectory is a common sub-trajectory

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Problem Statement

- Given a set of trajectories $I = \{TR_1, \ldots, TR_n\}$, the TraClus algorithm generates a set of clusters $O = \{C_1, \ldots, C_m\}$ as well as a representative trajectory for each cluster C_i
- Necessary definitions:
  - A *trajectory* is a sequence of multi-dimensional points, which is denoted as $TR_i = p_1 p_2 p_3 \ldots p_j \ldots p_{leni}$
  - A *cluster* is a set of trajectory partitions; a *trajectory partition* is a line segment $p_i p_j$ ($i < j$), where p_i and p_j are the points chosen from the same trajectory
  - A *representative trajectory* is an imaginary trajectory that indicates the major behavior of the trajectory partitions

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The Clustering Algorithm: *TRACLUS*

- Based on the partition-and-group framework

Algorithm **TRACLUS**
Input: A set of trajectories $I = \{TR_1, \ldots, TR_n\}$
Output: (1) A set of clusters $O = \{C_1, \ldots, C_m\}$
(2) A set of representative trajectories
Algorithm:
/* Partitioning Phase */
01: **for each** $TR \in I$ **do**
02: Partition TR into a set L of line segments;
03: Accumulate L into a set D;
/* Grouping Phase */
04: Group D into a set O of clusters;
05: **for each** $C \in O$ **do**
06: Generate a representative trajectory for C;

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Current Step (1/3)

Algorithm **TRACLUS**
/* Partitioning Phase */
01: **for each** $TR \in I$ **do**
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/* Grouping Phase */
04: Group D into a set O of clusters;
05: **for each** $C \in O$ **do**
06: Generate a representative trajectory for C;

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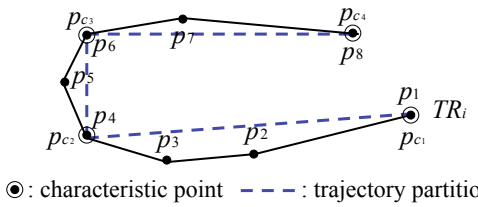
Characteristic Points

- Identify the points where the behavior of a trajectory changes rapidly; such points are called *characteristic points*

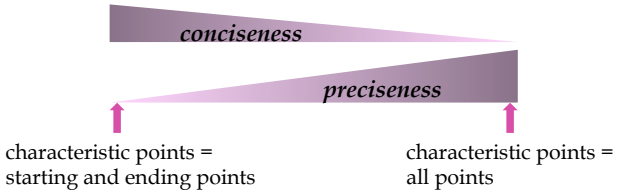


- A trajectory is partitioned at every characteristic point
- A line segment between consecutive characteristic points is called a *trajectory partition*

Desirable Properties of Trajectory Partitioning

- *Preciseness*: the difference between a trajectory and a set of its trajectory partitions should be as small as possible
- *Conciseness*: the number of trajectory partitions should be as small as possible

Note: two properties are contradictory to each other



⇒ We need to find the optimal tradeoff

Minimum Description Length (MDL) Principle

- The MDL principle has been widely used in information theory
- The MDL cost consists of two components [9]: ***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
  - $L(D \mid H)$ 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 $L(D \mid H)$

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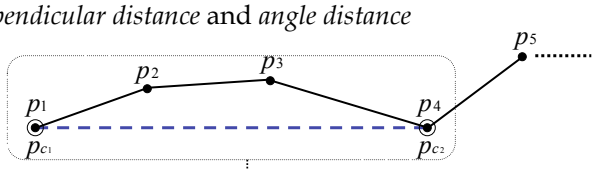
Translation into MDL Optimization

- Finding the optimal partitioning translates to finding the best hypothesis *using the MDL principle*
  - $H \Rightarrow$ a set of trajectory partitions, $D \Rightarrow$ a trajectory
  - $L(H) \Rightarrow$ the sum of the length of all trajectory partitions
  - $L(D \mid H) \Rightarrow$ the sum of the difference between a trajectory and a set of its trajectory partitions, computed by the combination of the *perpendicular distance* and *angle distance*



$$L(H) = \log_2(len(p_1p_4))$$
$$L(D \mid H) = \log_2(d_\perp(p_1p_4, p_1p_2) + d_\perp(p_1p_4, p_2p_3) + d_\perp(p_1p_4, p_3p_4)) + \log_2(d_\theta(p_1p_4, p_1p_2) + d_\theta(p_1p_4, p_2p_3) + d_\theta(p_1p_4, p_3p_4))$$

- $L(H)$ measures *conciseness*; $L(D \mid H)$ *preciseness*

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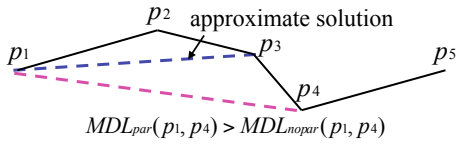
Approximate Trajectory Partitioning

- The cost of finding the optimal partitioning is prohibitive
- Use an approximate algorithm; our approximation is to regard the set of local optima as the global optimum
- Algorithm skeleton (see detail in the paper – Fig. 8):
  - Compute the MDL costs for the case when a point p_k is a characteristic point and the case when p_k is not

$$\begin{cases} \text{Choose } p_{k-1} \text{ as a characteristic point,} & \textit{if the former} > \textit{the latter} \\ \text{Advance } p_k \text{ by increasing } k, & \textit{otherwise} \end{cases}$$



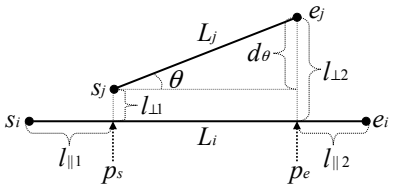
Current Step (2/3)

Algorithm **TRACLUS**
/* Partitioning Phase */
01: **for each** $TR \in I$ **do**
02: Partition TR into a set L of line segments;
03: Accumulate L into a set D;
/* Grouping Phase */
04: Group D into a set O of clusters;
05: **for each** $C \in O$ **do**
06: Generate a representative trajectory for C;

Distance between Line Segments

- The weighted sum of three components: the *perpendicular distance*($d_\perp$), *parallel distance*($d_\parallel$), and *angle distance*(d_θ)
  - Adapted from similarity measures used in the domain of pattern recognition [4]

$$dist(L_i, L_j) = w_\perp d_\perp + w_\parallel d_\parallel + w_\theta d_\theta$$



$$d_\perp = \frac{l_{\perp 1}^2 + l_{\perp 2}^2}{l_{\perp 1} + l_{\perp 2}}$$
$$d_\parallel = \mathrm{MIN}(l_{\parallel 1}, l_{\parallel 2})$$
$$d_\theta = \|L_j\| \times \sin(\theta)$$

Remark: the sum of the distances between endpoints does not work well for line segment clustering

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Density of Line Segments

- Change the density definitions for points, originally proposed for DBSCAN [6], to those for line segments
- **Def.** (*ε-neighborhood*):

  $N_\varepsilon(L_i) = \{L_j \in D \mid dist(L_i, L_j) \le \varepsilon\}$
- **Def.** (*core line segment*):

  L_i is a core line segment w.r.t. ε and *MinLns* if $|N_\varepsilon(L_i)| \ge MinLns$
- **Def.** (*directly density-reachable*):

  L_i directly density-reachable from L_j w.r.t. ε and *MinLns* if $L_i \in N_\varepsilon(L_j)$ and $|N_\varepsilon(L_j)| \ge MinLns$
- **Def.** (*density-reachable*):

  Transitive closure of directly density-reachability
- **Def.** (*density-connected set* $\equiv$ *cluster*):

  1) Maximal w.r.t. density-reachability

  2) Any line segments are density-connected, i.e., density-reachable from a third line segment

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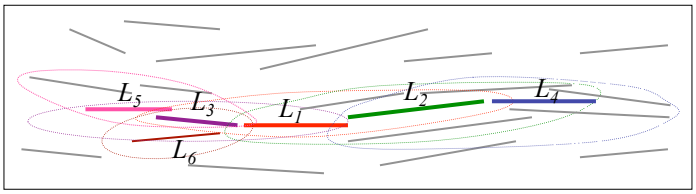
Density of Line Segments (cont'd)

- **Example**:
  - L_1, L_2, L_3, L_4, and L_5 are core line segments
  - L_2 (or L_3) is directly density-reachable from L_1
  - L_6 is density-reachable from L_1, but not vice versa
  - L_1, L_4, and L_5 are all density-connected

MinLns = 3



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

Note: the shape of an ε-neighborhood is likely to be an ellipse rather than a circle

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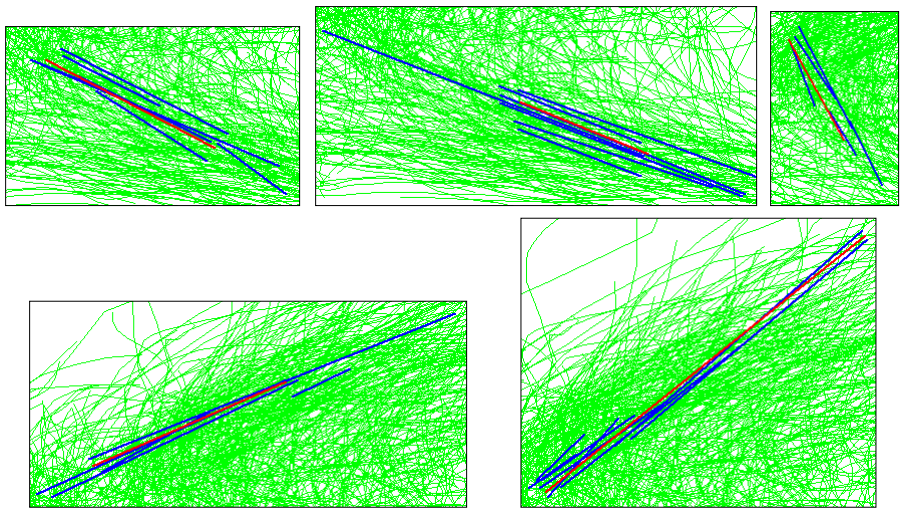
Examples of ε-neighborhoods



Red lines: core line segments, **Blue lines**: line segments in the ε-neighborhood

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Line Segment Clustering

- Algorithm skeleton (See Fig. 8 in the paper):
  1. Select an unprocessed line segment L
  2. Retrieve all line segments ***density-reachable*** from L w.r.t. ε and *MinLns*
     - If L is a core line segment ($|N_\varepsilon(L)| \geq MinLns$), a cluster is formed
     - Otherwise, L is marked as a noise
  3. Continue this process until all line segments have been processed
  4. Filter out clusters whose trajectory partitions have been extracted from too few trajectories

- Time complexity (See Lemma 3 in the paper):
  - $O(n^2)$: if an index does not exist
  - $O(n \log n)$: if an index does exist

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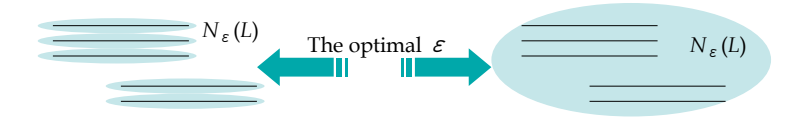
Heuristic for Parameter Value Selection

- **Estimation of ε**
  - Find the value of ε that minimizes the ***entropy*** of $|N_\varepsilon(L)|$ (ε-*neighborhood*)
    - Good clustering: $|N_\varepsilon(L)|$ tends to be skewed ⇒ the entropy is small
    - Worst clustering: $|N_\varepsilon(L)|$ tends to be uniform ⇒ the entropy is large



Too small ε → every $|N_\varepsilon(L)| = 1$

Too large ε → every $|N_\varepsilon(L)|$ = # of line segments

- **Estimation of *MinLns***
  - Choose one from $avg(|N_\varepsilon(L)|) + 1$, default MinLns ~ 3
    - *MinLns* should be larger than $avg(|N_\varepsilon(L)|)$ to discover meaningful clusters

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Current Step (3/3)

Algorithm **TRACLUS**
/* Partitioning Phase */
01: **for each** *TR* ∈ *I* **do**
02: Partition *TR* into a set *L* of line segments;
03: Accumulate *L* into a set *D*;
/* Grouping Phase */
04: Group *D* into a set *O* of clusters;
05: **for each** *C* ∈ *O* **do**
06: Generate a representative trajectory for *C*;

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Representative Trajectories

- Describe the overall movement of the trajectory partitions that belong to the cluster
- Correspond to common sub-trajectories
- Useful for domain experts to understand the movement in the trajectories

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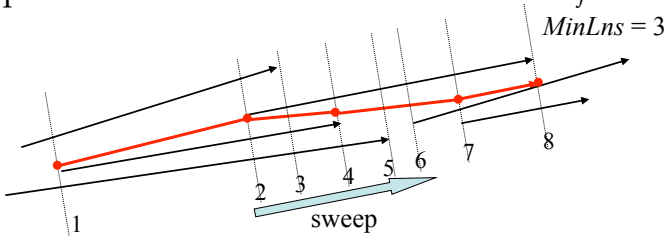
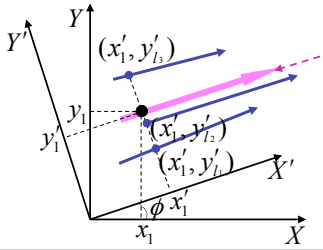
Representative Trajectory Generation

- Sweep a vertical line in the direction of the *major axis*



- Compute the average w.r.t. the *average direction vector*



average direction vector

average coordinate
in the $X'Y'$ coordinate system

$$(x_1', y_1') = (x_1', \frac{y_{l_1}' + y_{l_2}' + y_{l_3}'}{3})$$

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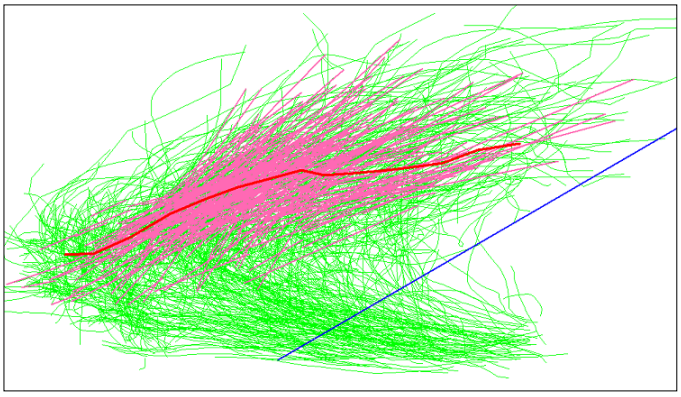
An Example of a Representative Trajectory



A red line: a representative trajectory,
A blue line: an average direction vector,
Pink lines: line segments in a density-connected set

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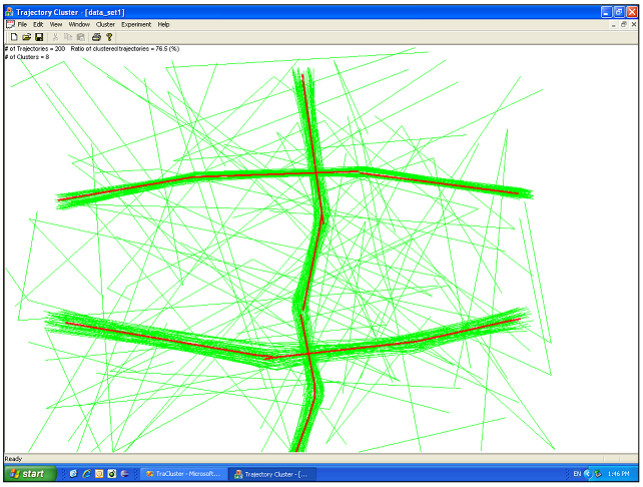
A Quick View of a Clustering Result



Simple synthetic data: 200 trajectories (25% are noises)

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Performance Evaluation

- Use two real trajectory data sets
  - Hurricane track data set
    - Record the Atlantic hurricanes from the years 1950 through 2004
    - Contain 570 trajectories and 17,736 points
  - Animal movement data set
    - Record the locations of elk, deer, and cattle from the years 1993 through 1996 (the Starkey project)
    - *Elk1993*: Contain 33 trajectories and 47,204 points;
      Deer1995: Contain 32 trajectories and 20,065 points

- Validate the clustering quality
  1) Estimate the parameter values for ε and *MinLns*
  2) Try a few values around the estimated ones; determine the optimal parameter values by visual inspection

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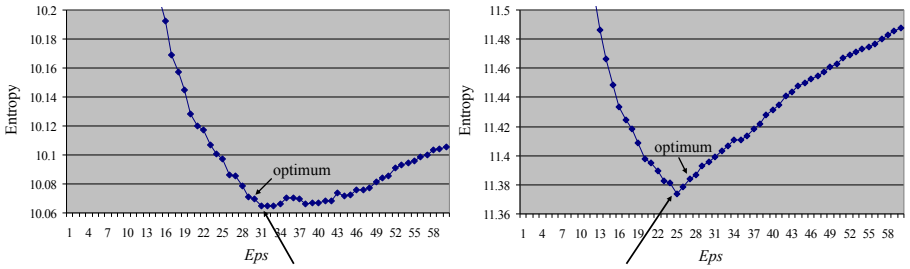
Effectiveness of Parameter Estimation

- Entropies depending on the value of ε



ε with the minimum entropy: an estimated value

(a) Hurricane Tracks (b) *Elk1993*

The optimal value is very close to the estimated value

⇒ The accuracy of the heuristic is quite high

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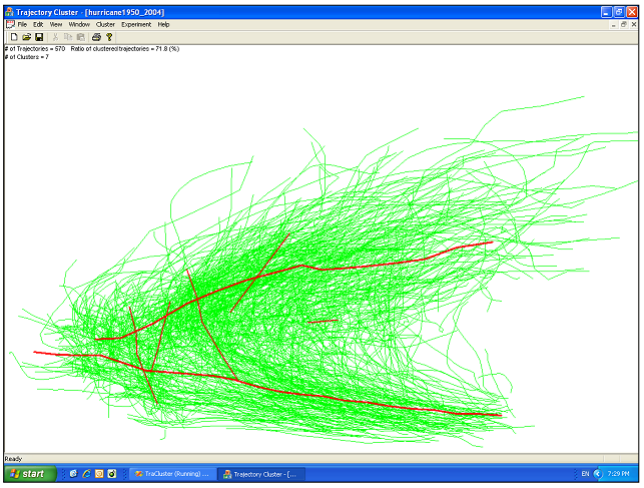
Clustering Result: Hurricane Tracks



ε = 30 and *MinLns* = 6 → # of clusters = 7

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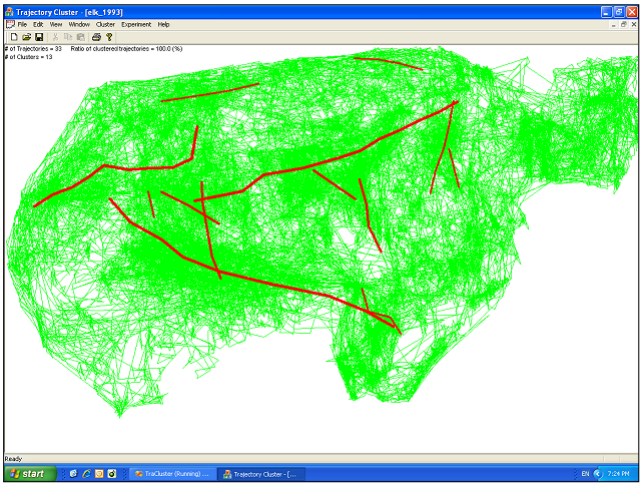
Clustering Result: *Elk1993*



ε = 27 and *MinLns* = 9 → # of clusters = 13

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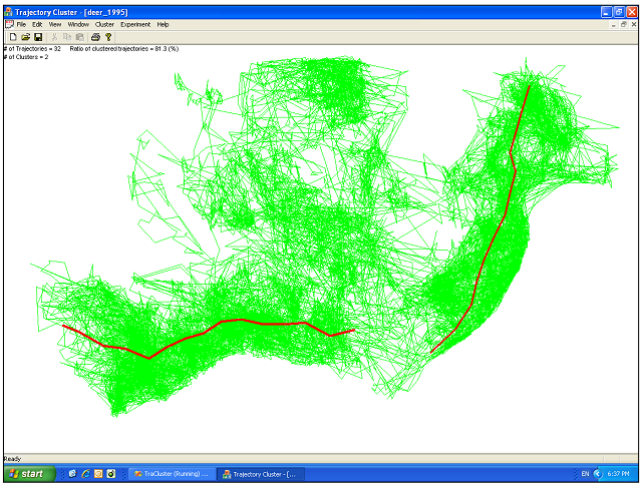
Clustering Result: *Deer1995*



ε = 29 and *MinLns* = 8 → # of clusters = 2

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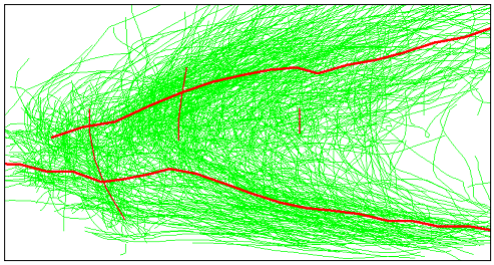
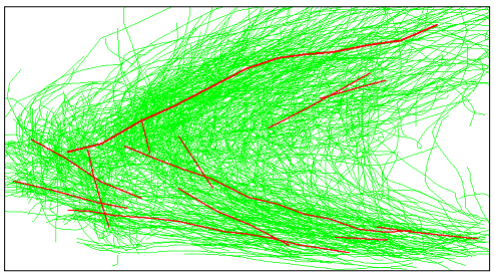
Effects of the Parameter Values

A larger ε or a smaller *MinLns* → a smaller number of larger clusters
e.g.,
ε = 33 and *MinLns* = 6 →
5 clusters (132 line segments)



A smaller ε or a larger *MinLns* → a larger number of smaller clusters
e.g.,
ε = 26 and *MinLns* = 6 →
13 clusters (31 line segments)



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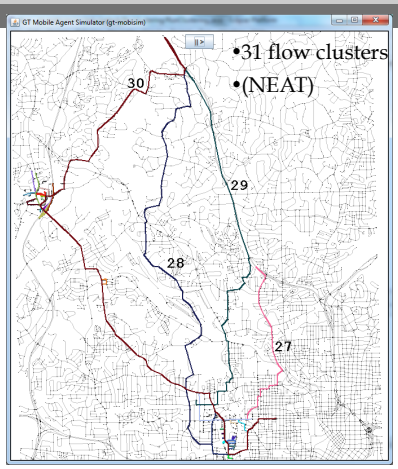
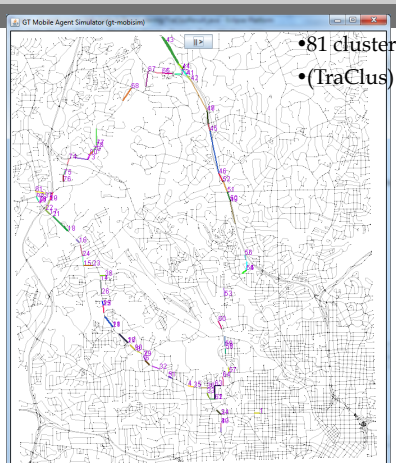
Problems with existing approaches



•31 flow clusters
•(NEAT)



•81 clusters
•(TraClus)

•Trajectories in road networks tend to have many sharp turns due to
•spatial constraints. Without road-network awareness, TraClus gen erates too many small clusters, high error ratio

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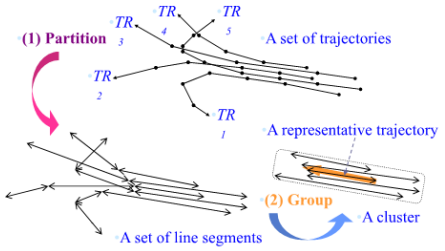
Trajectory Mining Research - State of the Art

❖ Clustering subtrajectories based on spatial correlations

➢Main idea: identify similar subtrajectories /spatial and temporal segments with hi gh density, which represent interesting movement patte rns/ areas of interest

➢TRACLUS (Lee et. al., 200 7): extends DBSCAN to clu ster sub-trajectories (partial clustering)

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



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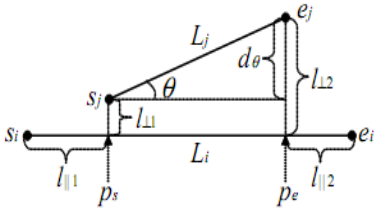
Measuring Similarity of Trajectories (Existing approaches)

- Criteria
  - Geometric shape / direction changes for partitioning
    - Geometric shape/ spatial proximity for grouping
- Euclidean-based distance

$$D(\tau_1,\tau_2)|_T = \frac{\int_T d(\tau_1(t),\tau_2(t))dt}{|T|},$$



$$d_\perp = \frac{l_{\perp 1}^2 + l_{\perp 2}^2}{l_{\perp 1} + l_{\perp 2}}$$

$$d_\parallel = \mathrm{MIN}(l_{\parallel 1}, l_{\parallel 2})$$

$$d_\theta = \|L_j\| \times \sin(\theta)$$

- *perpendicular distance,*
- *parallel distance*
- *angle distance*

Figure 5: Three components of the distance function for line segments.

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Georgia Tech College of Computing
Defining the New Face of Computing

DISL cercs

NEAT: Road-network aware trajectory clustering

Ling Liu
College of Computing,
Georgia Institute of Technology

•Binh Han, Ling Liu, Edward Omiecinski, IEEE TMC 2014, ICDCS 2012

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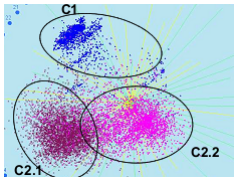
Clustering Mobile Object (MO) Trajectories

- **Goal:** Discover trajectory clusters representing major traffic flows and dense movement areas in road networks
- **Applications:** Urban planning, Public transit planning, Location-dependent advertising and entertainment
- **Unique Challenges**:
  - Distance for trajectories is different from distances for multi-dimensional points
    - Conventional data clustering algorithms fail to work with trajectories effectively
    - ➢ Harder to summarize MO trajectory data into interesting patterns through visualization



•Visualizing datasets of
•n-dimensional data points

NEAT approach

- a road-NEtwork Aware Trajectory clustering (NEAT) that considers:
  - Spatial constraints in a road network
    - Road segments
    - Road intersections
    - Speed limits
  - Traffic flow of objects moving among road segments
  - Network distance based proximity, i.e. shortest path distance
- Extensive experiments show that NEAT is efficient and offers high quality clusters compared to the traditional density-based approaches.

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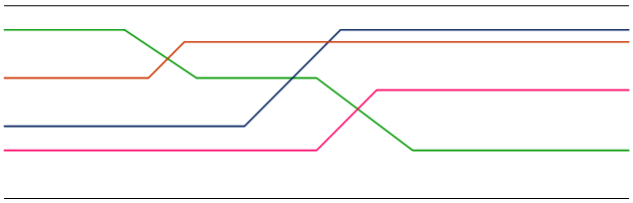
2. Overview – Design guidelines

- Example 1(traffic semantics): Given a set of objects moving along the same road segment.
  - They share similar movements wrt. the road network



•Trajectories within the same road segment should be grouped together regardless of their shapes of movement

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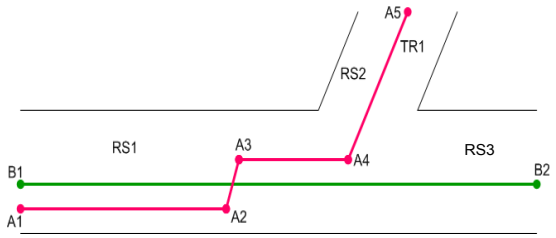
Overview – Design guidelines

- Example 2 (shape and direction changes):
  TR1 ={ A1A2, A2A3, A3A4, A4A5},
  TR2 = {B1B6}: No significant turning points

•TR2 is still needed to be split into 2 fragments at the road j unction.



•Only at the junctions, moving objects may make dramatic change of their movement

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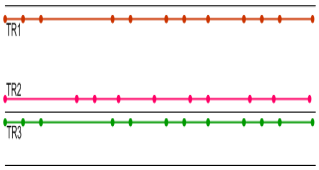
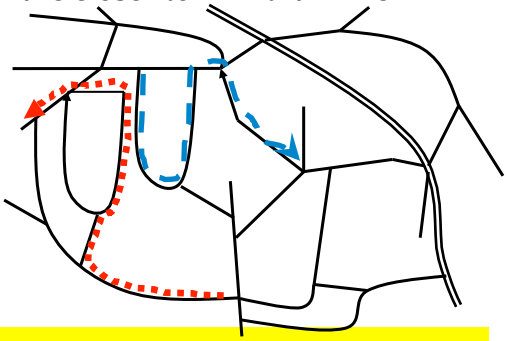
Overview – Design guidelines

- Example 3 (road network proximity):
  - In the Euclidean space: TR3 is closer to TR2 than TR1
  - In a road network: TR1 are closer to TR2 than TR3





•Use shortest path distance, instead of the Euclidean distance when measuring spatial similarity

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Overview: NEAT - Design guidelines

- Three road network aware mechanisms to capture MO trajectory similarities:
  - **Trajectory fragment:**
    - The road intersections are the initial partitioning points where a trajectory can be split into sub-trajectories, called trajectory fragments.
  - **Base Cluster:**
    - The trajectory fragments corresponding to a road segment can be viewed as a locally dense cluster of movement involved in the given set of trajectories.
  - **Flow Cluster**:
    - Merge trajectory fragments based on their continuity with regard to the traffic flows on consecutive road segments.

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Overview – Road-network model

- A **road network** is modeled as a directed graph G=(V, E):
  - V ={road intersections v} (i.e., nodes)
  - E = {road segments e} (i.e., edges)
- An **edge** *e = (sid, p, q): sid:* road segment Id, *p, q:* road junctions
  - $L_p(e)$*:* set of adjacent edges of e which connect to e at p
- A road network location l is a tuple (sid, x, y):
  - sid: id of the road segment contains this point belongs
  - (x,y): geometric coordinate of the point
- A trajectory TR is a sequence of points *TR = {trid,* $l_0 l_1 ... l_n$*}* capturing the locations of a MO in a road network over time and uniquely identified by *trid*
- A sub-trajectory is a subsequence of locations in a trajectory

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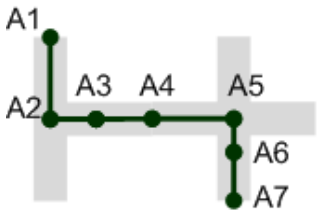
NEAT model – trajectory fragment

- t-fragment:
  - Given a trajectory $TR = \{trid, l_0 l_1 ... l_n\}$ and a road segment e, a ***t-fragment*** represents a sub-trajectory $l_k l_{k+1} ... l_{k+l}$ consisting of i+1 consecutive points in TR which lie on the same road segment, denoted by $tf = (trid, sid, l_k l_{k+i})$
  - Example:

TR = $A_1A_2 \ldots A_7$ has 3 t-fragments A_1A_2, A_2A_5 and A_5A_7



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NEAT model – Base Cluster

- Base cluster: A base cluster is a group of t-fragments (extracted from a given set of trajectories)which are located on the same road segmen

- The **density** of a base cluster S: d(S) = # t-fragments in S (cardinality of S).
- **dense-core**(B): the base cluster in B with the highest density
- **The netflow** between two base clusters Si and Sj = the number of trajectories participating in both clusters:

$$f(S_i, S_j) = |PTr(S_i) \oplus PTr(S_j)|$$

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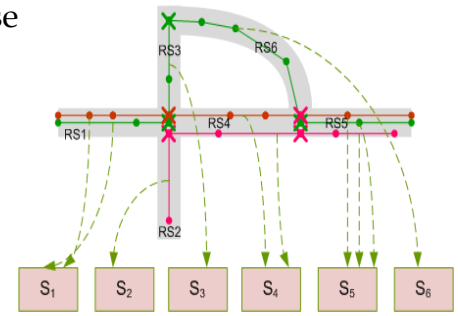
3.1 Base Cluster Formation

Algorithm Base_clusters_formation

- ✓Input: A set of MO trajectories T = {TR_1, TR_2, …,TR_N}
- ✓Output: A set of base

1. Trajectory splitting:
   - Trajectories → t-fragments
2. T-fragment grouping:
   - T-fragments → base clusters



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3.2 Flow cluster formation

- Flow-based approach: merging the base clusters using density and flow based metrics to form flow clusters

Algorithm Flow_based_clustering

- ✓Input: A set of base clusters B = {S_1, S_2, …,S_M}
- ✓Output: A set of flow clusters W = {F_1, F_2, …, F_Q}
- ✓Three tasks:
  - **Density based initialization,**
  - **f-Neighbor based merging,**
  - **Flow-correlation based termination**

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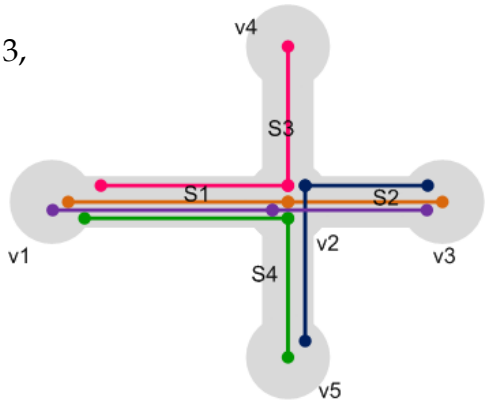
NEAT model: An example

- A set of base clusters: B={S_1, S_2, S_3, S_4}
- Density: d(S_1) = 4, d(S_2)= 3, d(S_3) = 1, d(S_4) = 2
- S_1 =dense-core(B)
- netflow: f(S_1,S_2) = 2
- *f*-neighborhood: $N_f(S_1, v_2)$={ S_2, S_3, S_4}
- MaxFlow(S_1, v_2) = {S_2}
- F={S_1,S_2} is a flow cluster
- f(F,S_3) = 1, f(F,S_4) = 2



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NEAT model – Flow Cluster

Let S_i be a base cluster and *p* denote one endpoint of e^{Si}(the road segment associated with S_i).

- The *f*-neighborhood of S_i *wrt. p*:

$$N_f(S_i, p)=\{S_j \mid e^{Sj} \text{ in } L_p(e^{Si}) \ \& \ f(S_i, S_j) > 0\}$$

- MaxFlow neighbor S_j of S_i wrt. *P*:

$$f(S_i, S_j)= maxflow(S_i,p) = max\ \{f(S_i, S_k)\} \mid S_k \text{ in } N_f(S_i, p)\}.$$

- A **flow cluster** is a spatially ordered list of base clusters, denoted by F = {$S_0S_1…S_N$} such that S_{i+1}in $N_f(S_i)$ and $e^{S0}e^{S1}...e^{SN}$ forms a route in the road network

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Flow-based clustering

- Choose a base cluster to merge with another base cluster S:
  - The f-neighborhood S_j in $N_f(S, u)$ are the candidates to be merged with S
  - Consider the flow, density and speed limit of all f-neighborhood of S to decide which f-neighbor should be merged with S
    - Flow factor: $q = \frac{f(S, S_j)}{|PTr(S)|}$
    - Density factor: $k = \frac{d(S_j)}{d(S) + \sum_{S_i \in N_f(S, n_u)} d(S_i)}$
    - Speed factor: $v = \frac{speed(S_j)}{\sum_{S_i \in N_f(S, n_u)} speed(S_i)}$

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Flow cluster formation

Choose a base cluster S_j in $N_f(S, p)$ to merge with S:

- Compute the merge selectivity of a base cluster S_j in $N_f(S, p)$,

$$SF = w_q \times q + w_k \times k + w_v \times v$$

•Flow factor density factor, speed factor

- Choose S_j if $SF(S_j)$ is the largest compared to all other f-neighborhood clusters.
- The weights $w_q > 0$, $w_k >= 0$, $w_v >= 0$ are determined by applications and $w_q + w_k + w_v = 1$

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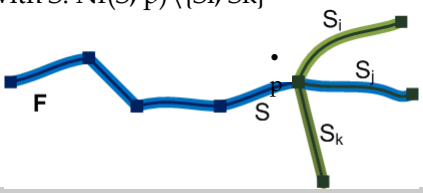
Flow cluster formation

- If we want to emphasize the flow factor, the weights are set as follows:

$$w_q = 1,\ w_k = w_v = 0$$

- The MaxFlow neighbor of S will be chosen to merge with S
- Each merging step: check the flow correlation:
  - Compute maxflow(S) = f(S, S_i)
  - If f(S, Si)/ f(Si, Sk) < β :
    - the flow (Si, Sk) is dominant.
    - Candidates to merge with S: Nf(S, p)\{Si, Sk}



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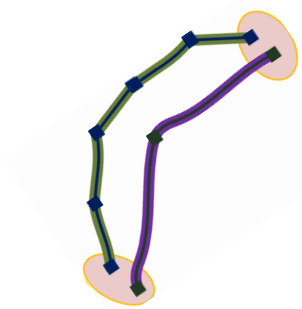
Flow Cluster Refinement

- Exploit opportunities to further merge some flow clusters generated from Phase 2:
  - flow clusters whose ending locations are close in terms of shortest path distance

→ Density-based grouping



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Phase 3: NEAT Optimization → Density based Clustering Refinement

- We make an adaptation to the DBSCAN:
  (1) the data unit to be clustered is a flow cluster
  (2) no minimum cluster cardinality is required
  (3) the distance function is our modified Hausdorff distance between flow clusters:

$$\begin{aligned} dist_N(F_i, F_j) &= dist_N(r_{F_i}, r_{F_j}) \\ &= max\{max_{a\in\{a_1,a_2\}} min_{b\in\{b_1,b_2\}} d_N(a,b), \\ &\quad max_{b\in\{b_1,b_2\}} min_{a\in\{a_1,a_2\}} d_N(b,a)\} \end{aligned} \quad (5)$$

where d(a,b) is the shortest path from point a to point b

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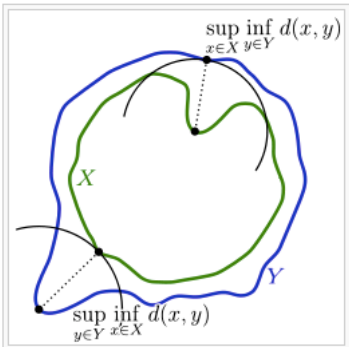
Hausdorff Distance

- Let X and Y be two non-empty subsets of a metric space (M, d). We define their Hausdorff distance $d_H(X, Y)$ by

$$d_H(X,Y) = \max\{\sup_{x\in X}\inf_{y\in Y} d(x,y), \sup_{y\in Y}\inf_{x\in X} d(x,y)\},$$

where *sup* represents the supremum and *inf* the infimum.



Components of the calculation of the Hausdorff distance between the green line *X* and the blue line *Y*.

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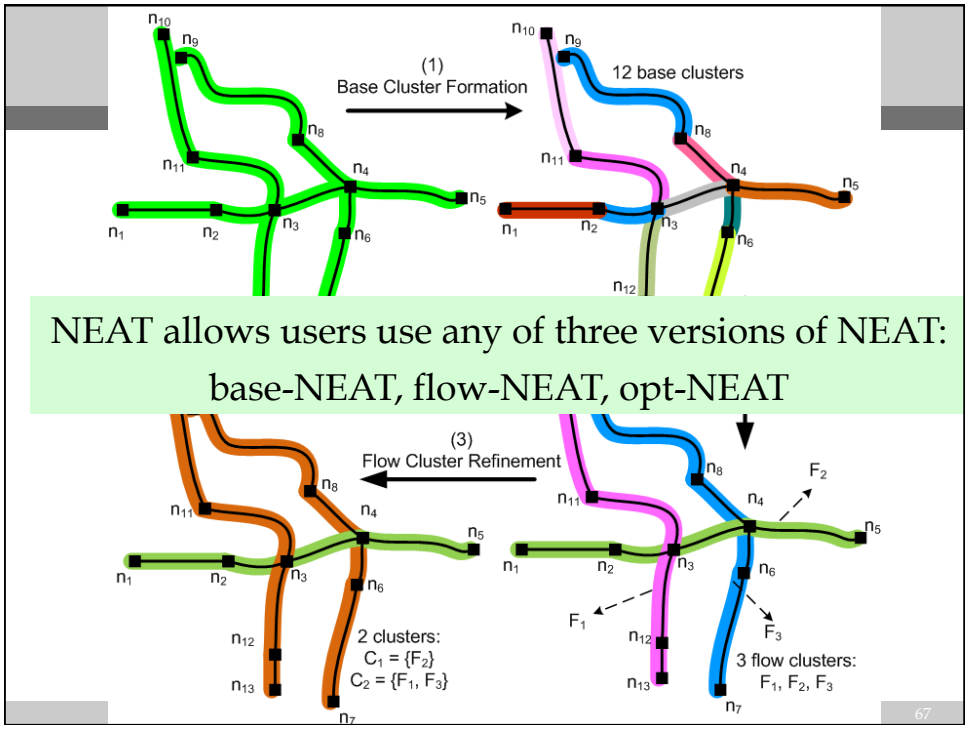

Computation Optimizing

- Density-based grouping:
  - For each pair of flows (F_i, F_j), compute $dist_N(F_i, F_j)$
  - $dist_N(F_i, F_j) < \varepsilon$: density-connected → grouping opportunity
- Problem: shortest path distance computation is expensive

$$O(nlogn + m)$$

- Solution: use Euclidean Lower Bound filtering to reduce the number of shortest path distance computation
  - Given the ELB: $dist_E(F_i, F_j) \leq dist_N(F_i, F_j)$
  - Only compute $dist_N(F_i, F_j)$ when $dist_E(F_i, F_j) \leq \varepsilon$
- Effective for real time trajectory clustering

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NEAT framework: Summary

NEAT framework includes three phases:

(1) Base Cluster Formation

Each trajectory is partitioned into t-fragments.

The t-fragments which belong to the same road segment are grouped together into a *base cluster*.

(2) Flow Cluster Formation (Flow-based Clustering)

The base clusters are merged into larger clusters considering their density and continuities.

(3) Flow Cluster Refinement

We optimize the flow-based clustering results in a density-based process.

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Experiments –Datasets and setup

- Maps: NW Atlanta, San Jose, Miami

Regions	Total length	# Segments	# Junctions	Avg. segment length	Junction degree
North West Atlanta, GA	1384.4km	9187	6979	150.7m	avg: 2.6, max: 6
West San Jose, CA	1821.2km	14600	10929	124.7m	avg: 2.7, max: 6
Miami-Dade, FL	26148.3km	154681	103377	169.0m	avg: 3.0, max: 9

- Synthesized Datasets: generated using GT-MobiSIM trace generator

Datasets	Number of points		
	ATL	SJ	MIA
ATL/SJ/MIA500	114878	131982	276711
ATL/SJ/MIA1000	233793	255162	452224
ATL/SJ/MIA2000	468738	542598	893412
ATL/SJ/MIA3000	669924	794638	1302145
ATL/SJ/MIA5000	1277521	1296739	2262313

- Implemented using Java, run on PC Intel CPU 2.00GHz with 1 GB main memory allocated for the Java heap size

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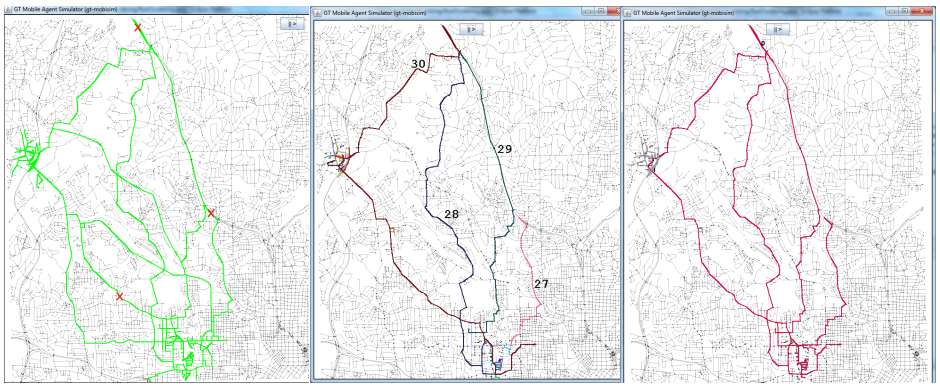
NEAT result visualization



•a) Input data: ATL500

•b) 31 flow clusters

•c) 2 clusters after optimizing ph ase

•(eps=6500)

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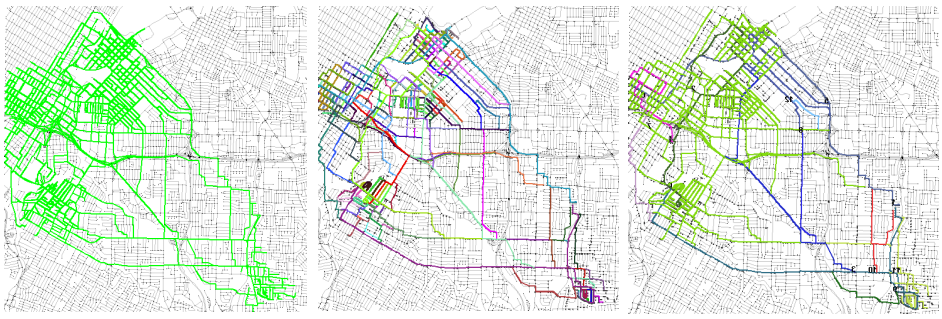
Results for San Jose datasets



•a) Input: SJ5000

•b) 172 flow clusters

•c) 13 clusters after
•optimizing phase
•with eps = 1200

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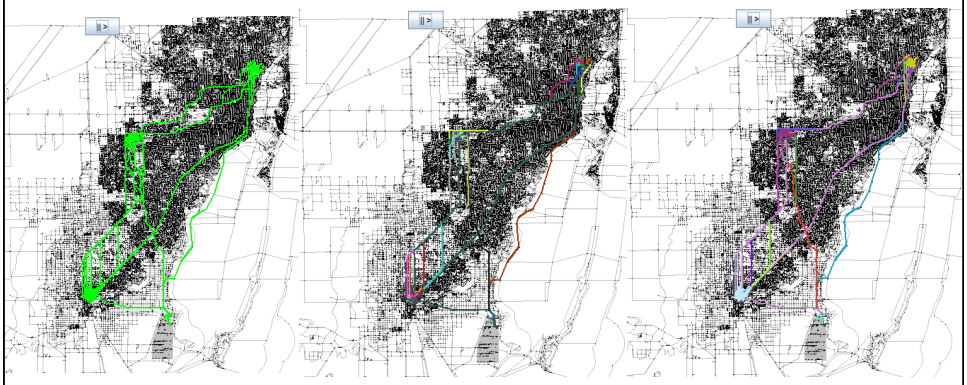
Results for Miami datasets



•a) Input: MIA3000

•b) 300 flow clusters

•c) 33 clusters after
•optimizing phase
•with eps = 2000

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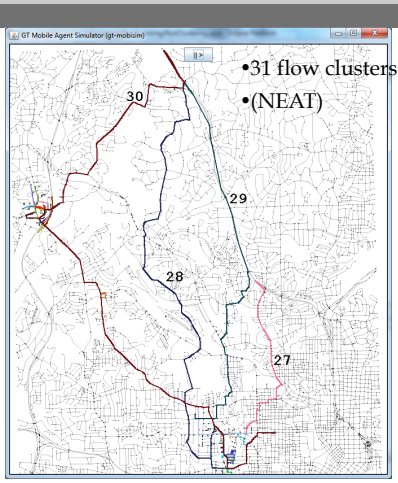
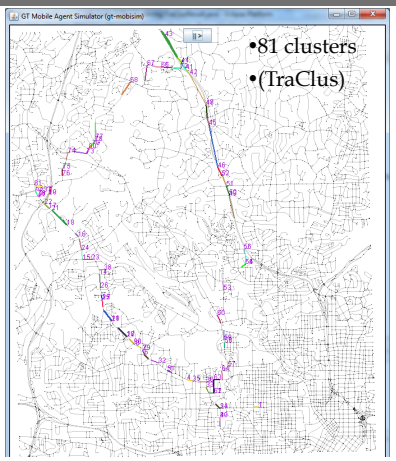
Efficiency and effectiveness of NEAT



•31 flow clusters
•(NEAT)



•81 clusters
•(TraClus)

•TraClus: does not merge well, small cardinality clusters, misses important routes

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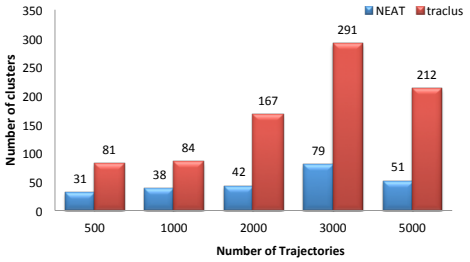
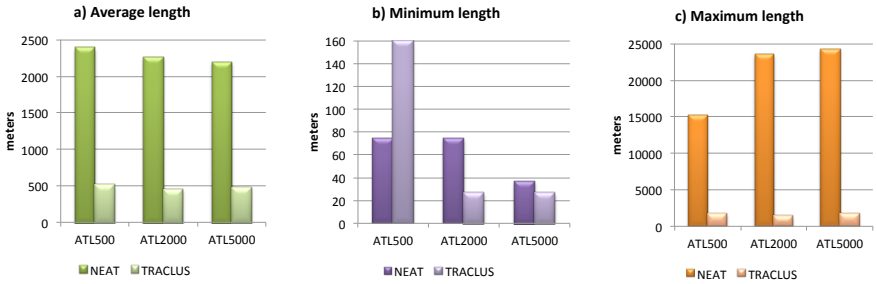
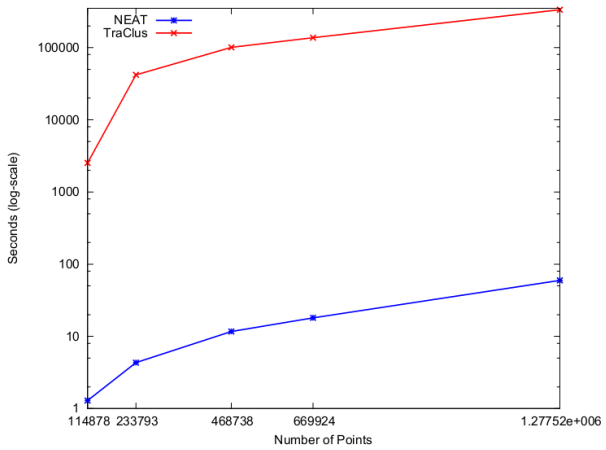
Accuracy



•NEAT merges better: trajectory clusters represent highly dense and continuous traffic flows (long routes)

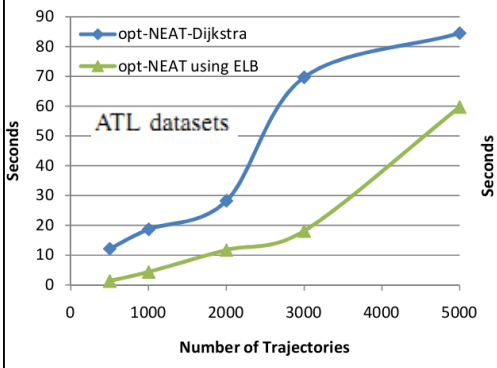


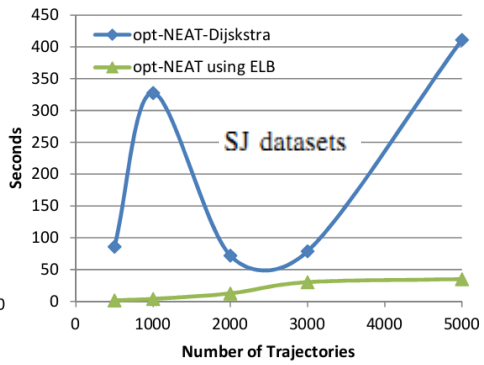
Efficiency



- NEAT is 3 orders of magnitude faster
- NEAT uses base cluster as building blocks instead of points and line segments
- No distance computation is required in basic NEAT approach

Effectiveness of using Euclidean Lower Bound





Datasets	ATL500	ATL1000	ATL2000	ATL3000	ATL5000	SJ500	SJ1000	SJ2000	SJ3000	SJ5000
# flow clusters	31	37	42	79	49	73	156	55	52	180

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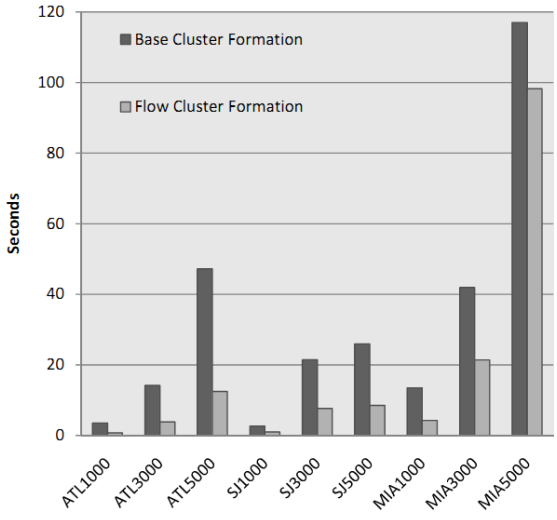
Performance of NEAT component Algorithms



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NEAT Trajectory Clustering – Highlights

- The base cluster and flow cluster are the key elements in our NEAT model to capture the features of the traffic from the given trajectories
- *t*-fragment and *f*-neighborhood are used to identify the most critical and interesting parts of the trajectories
- NEAT devises the merging process by carefully combining the density and the continuity of traffic in the road network to improve the clustering quality

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Thank You!

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