
# Mobility Data Exploration

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*From bulks of location data to useful trajectory aggregations and patterns*

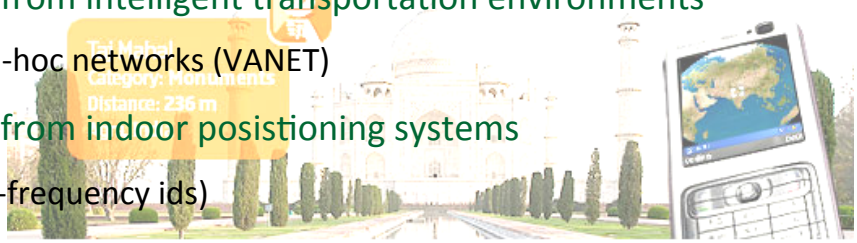
# Mobile devices and services

- Large diffusion of mobile devices, mobile services and location-based services ➔ **mobility data**



# Which mobility data?

- Location data from mobile phones
  - i.e., cell positions in the GSM/UMTS network
- Location data from GPS-equipped devices
  - Humans (pedestrians, drivers) with GPS-equipped smartphones
  - Vessels with AIS transmitters (due to maritime regulations )
- Location data from intelligent transportation environments
  - Vehicular ad-hoc networks (VANET)
- Location data from indoor posistioning systems
  - RFIDs (radio-frequency ids)
  - Wi-Fi access points
  - Bluetooth sensors



# GPS Data

- Raw data: GPS recordings

```
N; Time; Lat; Lon; Height; Course; Speed; PDOP; State; NSat
…
8;22/03/07 08:51:52;50.777132;7.205580; 67.6;345.4;21.817;3.8;1808;4
9;22/03/07 08:51:56;50.777352;7.205435; 68.4;35.6;14.223;3.8;1808;4
10;22/03/07 08:51:59;50.777415;7.205543; 68.3;
11;22/03/07 08:52:03;50.777317;7.205877; 68.8;
12;22/03/07 08:52:06;50.777185;7.206202; 68.1;
13;22/03/07 08:52:09;50.777057;7.206522; 67.9;
14;22/03/07 08:52:12;50.776925;7.206858; 66.9;
15;22/03/07 08:52:15;50.776813;7.207263; 67.0;
16;22/03/07 08:52:18;50.776780;7.207745; 68.8;
17;22/03/07 08:52:21;50.776803;7.208262; 71.1;
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…
```
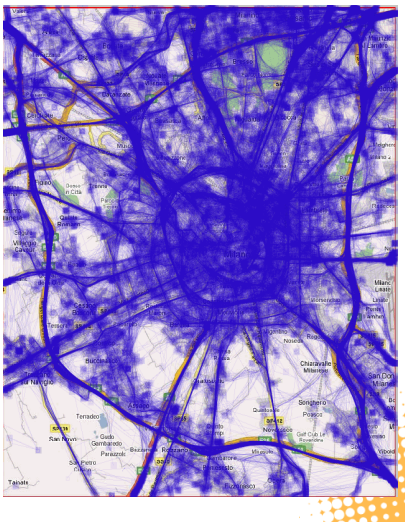
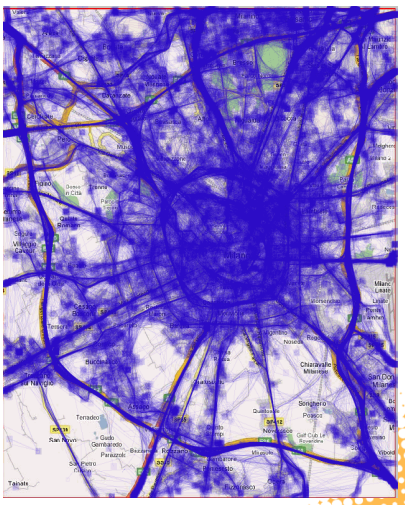





# Key questions that arise

- What kind of **analysis** is suitable for mobility data?
  - In particular, trajectories of moving objects?
  - How does infrastructure (e.g. road network) affect this analysis?
- Which **patterns / models** can be extracted out of them?
  - Clusters, frequent patterns, anomalies / outliers, etc.
  - How to compute such patterns / models efficiently?



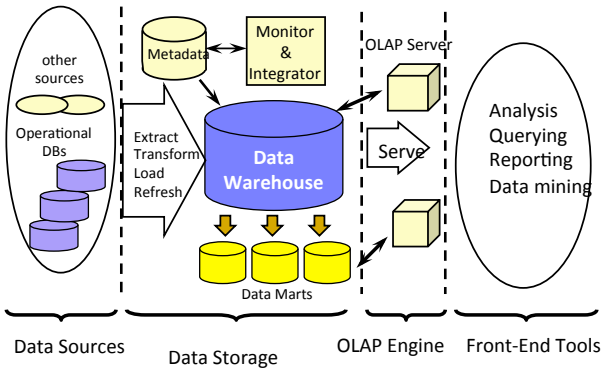
# part I: OLAP analysis



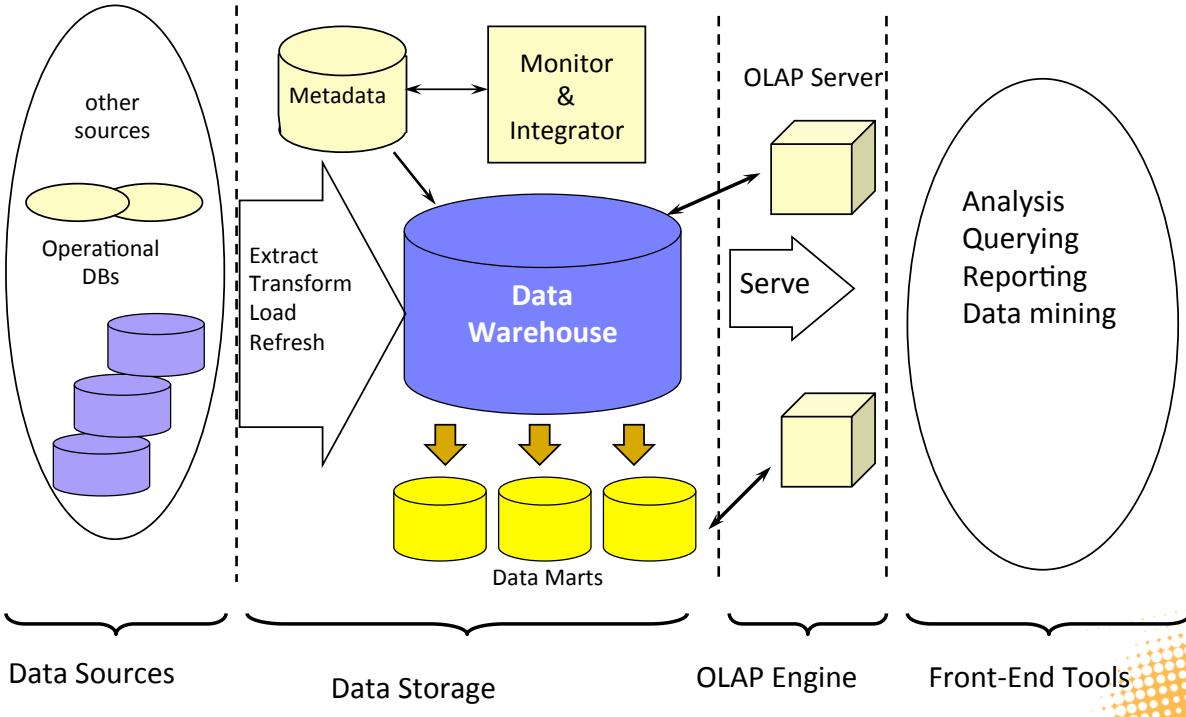
## Data warehousing (DW)

- Widely investigated for conventional, non-spatial data.
- A widely accepted definition:
  - A Data Warehouse (DW) is a subject-oriented, integrated, time-variable, non-volatile information system aiming at decision making.

    B. Inmon (1992) *Building the Data Warehouse*. 1st Edition. Wiley and Sons.



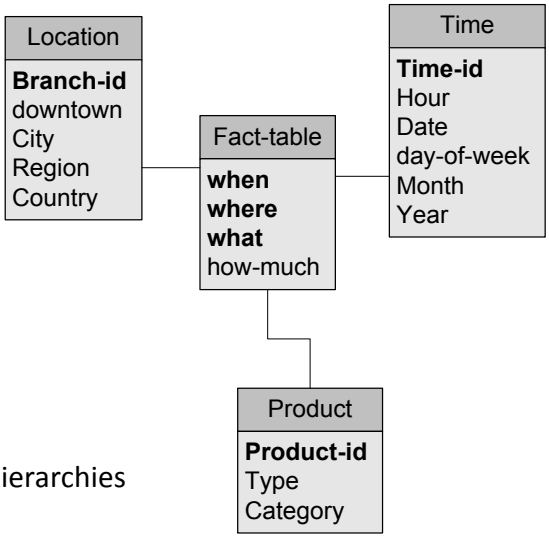
# DW architecture






# Aggregating DB information: Data Cubes

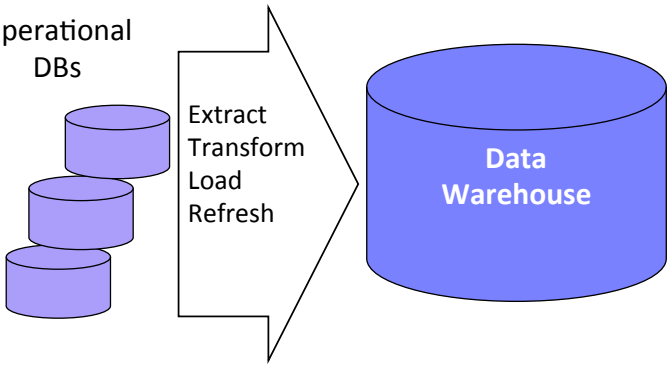
- Aggregated information from DBs is stored in **data cubes** [Gray et al. DMKD '97]
  - Feeded from DB via an Extract-Transform-Load (ETL) procedure
  - Technically, a collection of relations (if relational model is adopted)
- Typical structure: **star schema**
  - Several **dimension tables** with their hierarchies
  - One **fact table** with **measures**
  - Variation: constellation schema (more than one fact tables)



# ETL example

- DB schema

```
product (product_ID,
   type, category)
location (branch_ID,
   downtown, city,
   region, country)
sales-transaction (
   timestamp, product_ID,
   branch_ID, units_sold,
   unit_price)
```



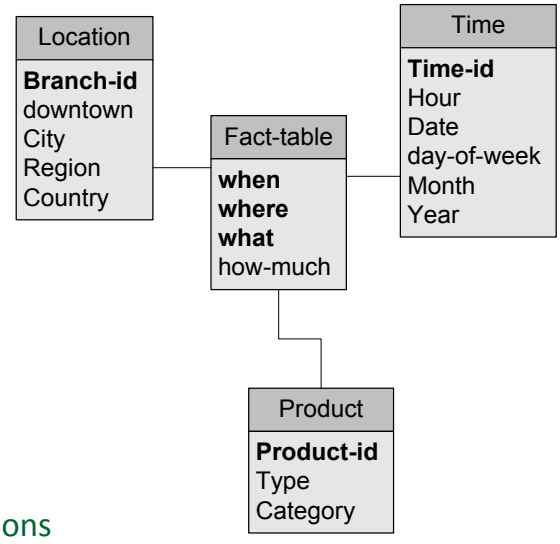

- ETL query

```
INSERT INTO sales
   ( SELECT datetime(timestamp) AS when,
            branch_ID AS where, product_ID AS what,
     sum(units_sold*unit_price) AS how-much
     FROM sales-transaction
     GROUP BY when, where, what
     HAVING how-much > 0 )
```



# OLAP operations on data cubes

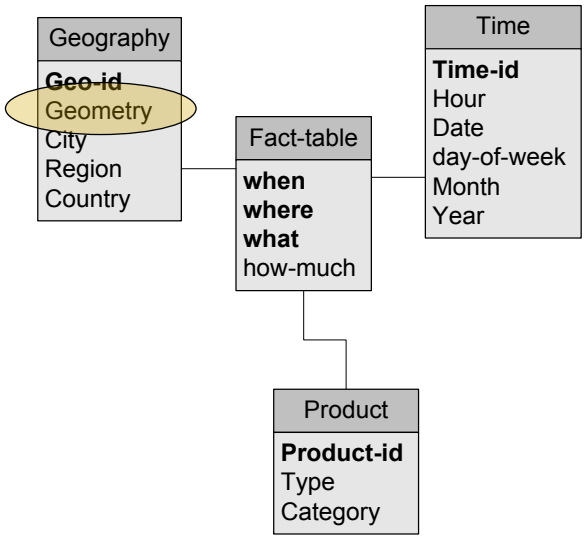
- A sequence of operations:
  - (**roll-up**) "What was the total turnover ("how-much" measure) per month and per city?"
  - (**slice**) "Especially in March, what was the turnover per city?"
  - (**drill-down**) "Especially in March, what was the turnover on weekdays vs. weekends?"
  - (**cross-over**) "Display the DB records that support the above result."




- Degree of efficiency of OLAP operations depends on the type of measures
  - distributive vs. algebraic vs. holistic

# Data cubes for spatial data

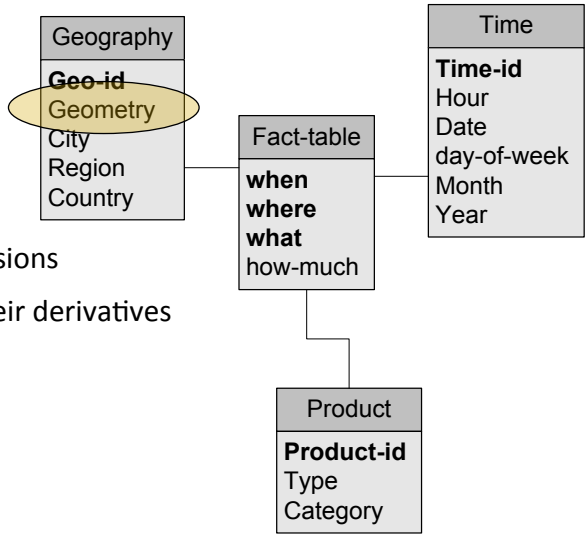
- **Spatial data cubes**
  [Han et al. PAKDD'98]
  - Dimensions
    - Spatial (e.g. Geography) vs.
    - non-spatial /thematic
      (e.g. Time, Product)
  - Measures:
    - Numerical vs. Spatial



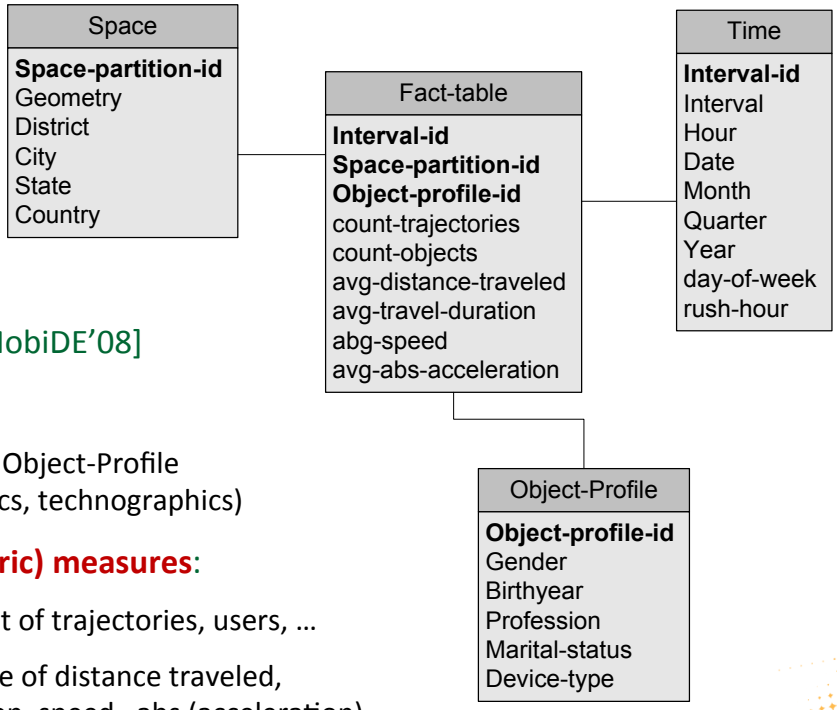



# Data cubes for trajectory data

- **Trajectory data cubes**
  [Orlando et al. JCSE'07]
  [Marketos et al. MobiDE'08]
  - extract aggregate information
    from MOD
  - temporal, spatial, thematic dimensions
  - measures over space, time and their derivatives



# An example data cube for trajectories



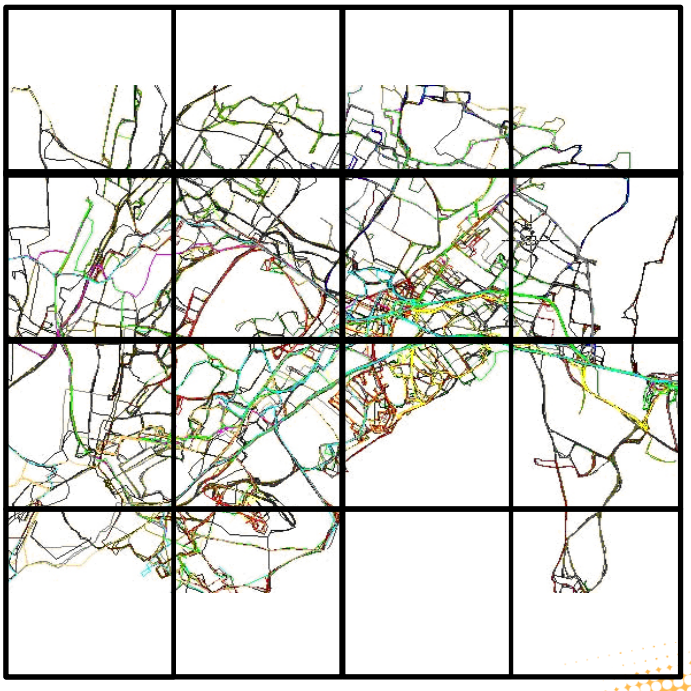

[Marketos et al. MobiDE'08]

- **3 Dimensions**:
  - Space, Time, Object-Profile (demographics, technographics)
- **Several (numeric) measures**:
  - Distinct count of trajectories, users, …
  - Average value of distance traveled, travel duration, speed, abs (acceleration), …



# Issues that arise

- During ETL:
  - how to **efficiently** feed the fact table?
    - Aggregations over the MOD
- During OLAP:
  - how to address the "**distinct count problem**"?
    - the same trajectory may pass multiple times from the same cell



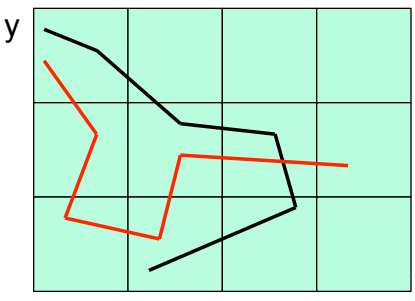
# ETL processing: loading

- Loading data into the dimension tables ➔ straightforward
  - Of course, choosing a reasonable **resolution** in space/time is critical
  - (as usual) tradeoff between quality and usage of resources



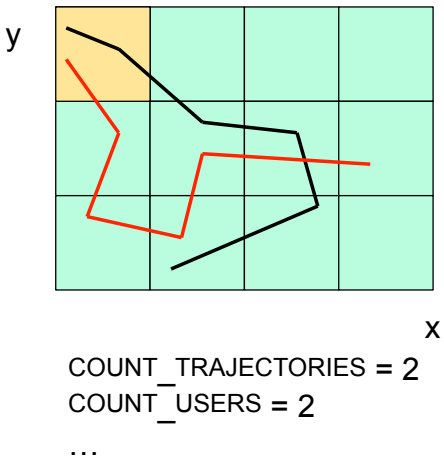
# ETL processing: loading

- Loading data into the fact table ➔ complex, expensive
  - Fill in the measures with the appropriate numeric values
  - In order to calculate the measures, we have to extract the portions of the trajectories that fit into the base cells of the cube
    - alternative solutions:
      - cell-oriented
      - trajectory-oriented



# ETL processing: algorithms

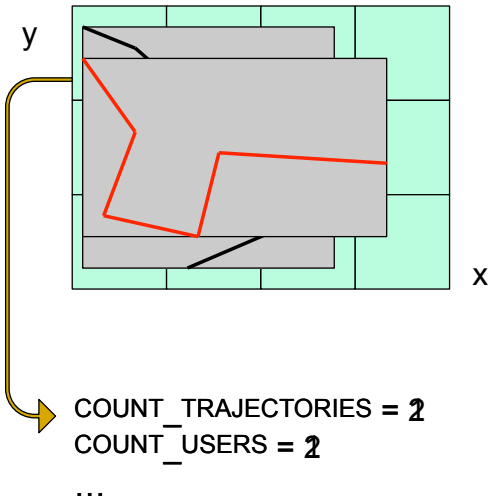
- **Cell-oriented approach (COA)**
  - Search for the portions of trajectories that reside inside a s/t cell
    - **spatiotemporal range query**
    - efficiently supported by the **TB-tree** [Pfoser et al. 2000]
  - Decompose the trajectory portions with respect to the user profiles they belong to
  - Compute measures for this cell
  - Repeat for the next cells






# ETL processing: algorithms

- **Trajectory-oriented approach (TOA)**
  - Discover the s/t cells where each trajectory resides in
    - Prune by using the trajectory MBR
  - Compute measures for each cell
  - Repeat for the next trajectories



# OLAP (aggregation in space/time)

- The problem:
  - A trajectory may contribute to several cells
  - What happens when rolling-up?
- The "**distinct count problem**" (Tao et al. 2004)



# The distinct count problem

**At the lowest hierarchy level:**

count of trajectories in $R_{1,1}$ = 2

count of trajectories in $R_{1,2}$ = 2

count of trajectories in $R_{2,1}$ = 1

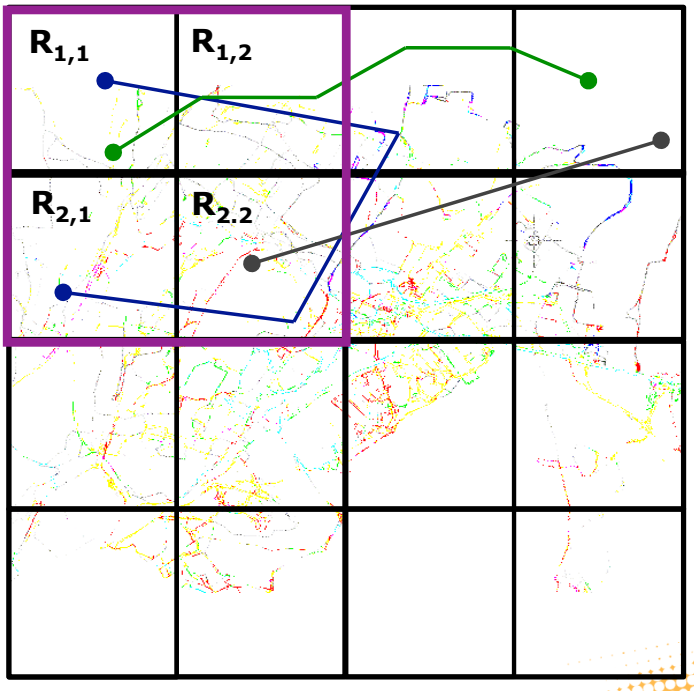
count of trajectories in $R_{2,2}$ = 2

**Roll up in R = $R_{1,1} \cup R_{1,2} \cup R_{2,1} \cup R_{2,2}$**

count of trajectories in R = 7 (according to traditional roll-up)

whereas the correct is 3 !!

**Any idea how to estimate the correct answer?**



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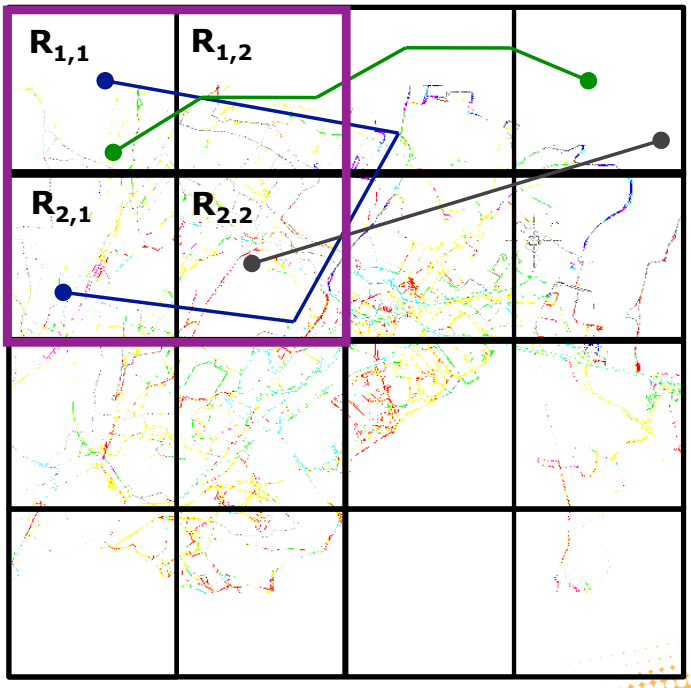
**$R_{1,1} \cup R_{1,2} \cup R_{2,1} \cup R_{2,2}$**

count of trajectories in R = 7
(according to traditional roll-up)

whereas the correct is 3 !!

A (suboptimal) solution:
(Orlando et al. 2007a; 2007b)

"Keep a note on the border between cells"






# Case study

*Observe and analyze traffic flow during a week in Milano*

U. Venice & U. Piraeus,
GeoPKDD final meeting, Pisa, May 2009

T-Warehouse tool (Leonardi et al. 2010)

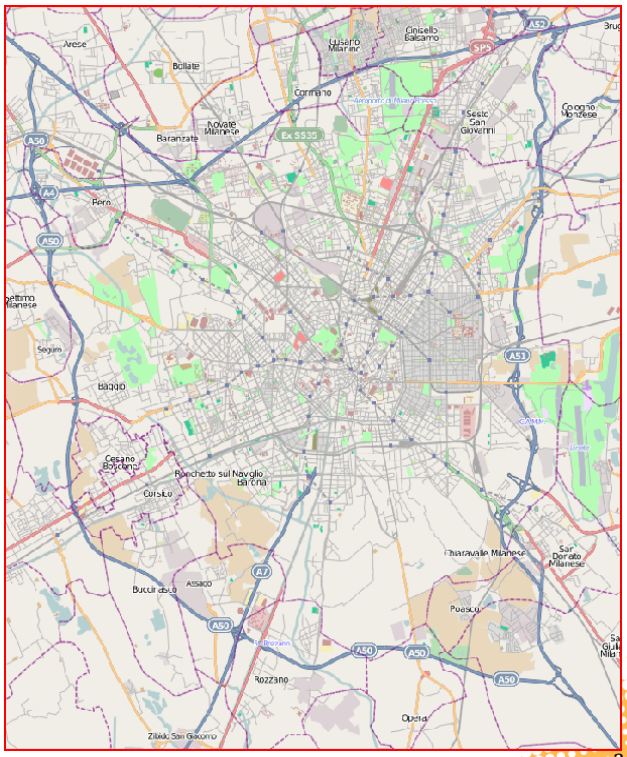
# Typical kinds of analysis (from end-users' point of view)

- How does traffic flow and speed change along the week?
  - Q1: Where does the highest traffic appear? at what hour?
  - **A1: unclassified choropleth map (for a specific period of time)**
  - Q2: What exactly happens at the road network level?
  - **A2: drill-downs in space and/or time**
  - Q3: How does movement propagate from place to place?
  - **A3: data cube measures' correlation (speed vs. presence)**



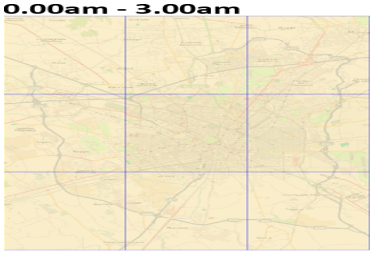
# Milano dataset

- What?
  - 2M observations (GPS recordings)
    - for 7 days (Sun. 1 - Sat. 7 April '07)
  - 200K trajectories (after reconstruction)
- How?
  - Stored in Hermes MOD engine
  - Feeding a trajectory data cube

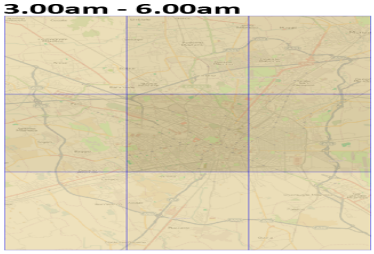


# Presence on Tuesday
## (aggregated level)

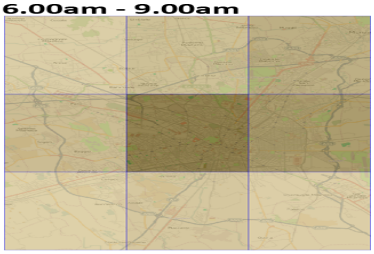
0.00am - 3.00am



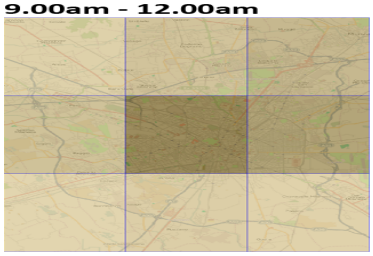
3.00am - 6.00am



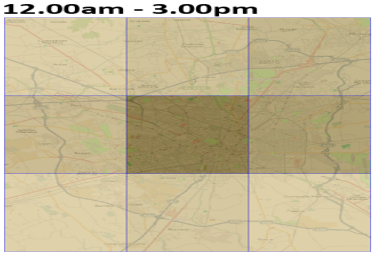
6.00am - 9.00am



9.00am - 12.00am



12.00am - 3.00pm



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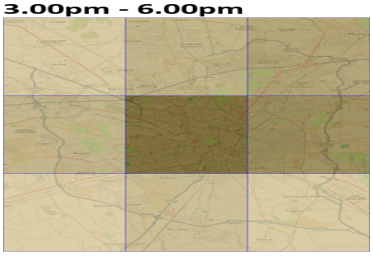

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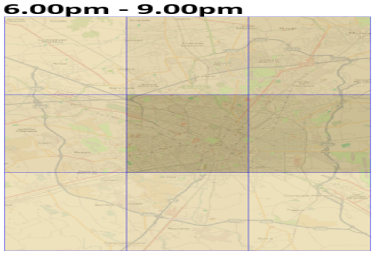
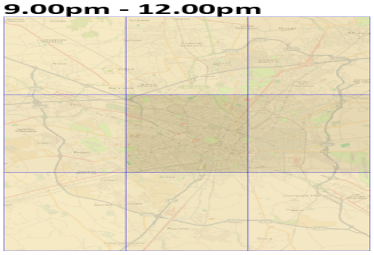


9.00pm - 12.00pm





# Presence on Saturday
## (aggregated level)

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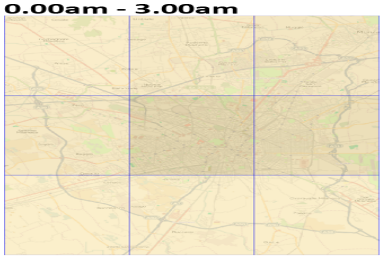
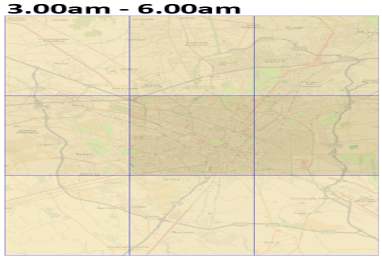
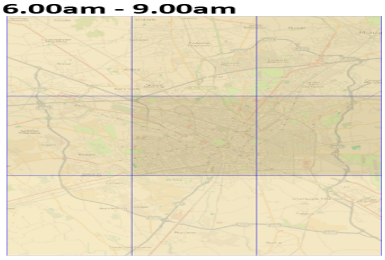


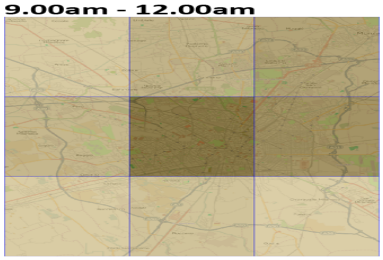
3.00am - 6.00am



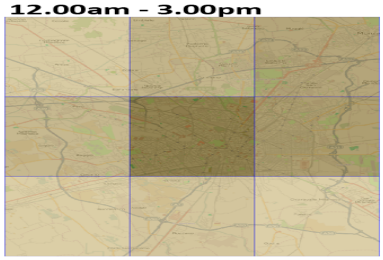
6.00am - 9.00am



9.00am - 12.00am



12.00am - 3.00pm



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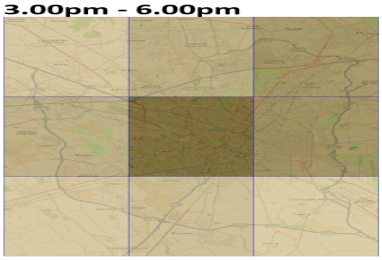

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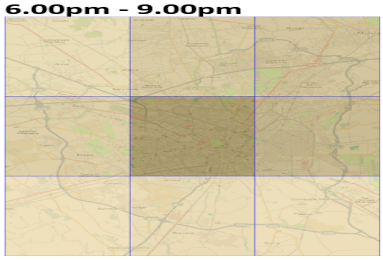

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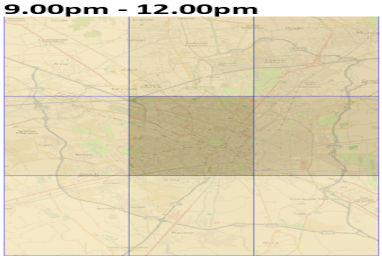
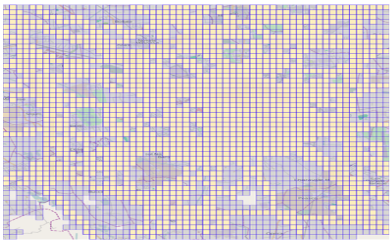
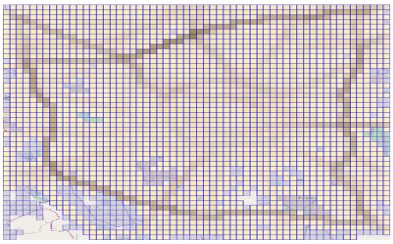


# Presence on Tuesday
## (road network level)

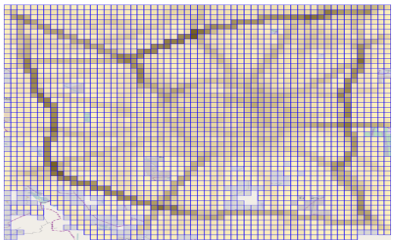
0.00am - 3.00am



3.00am - 6.00am



6.00am - 9.00am



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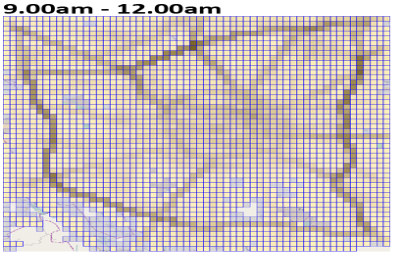
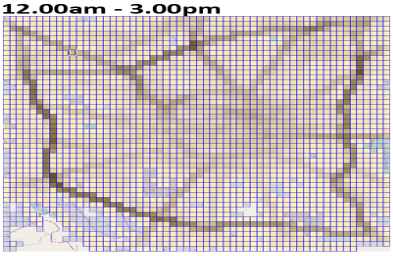
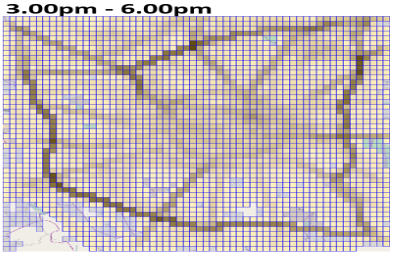


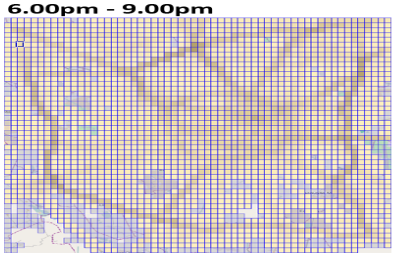
12.00am - 3.00pm



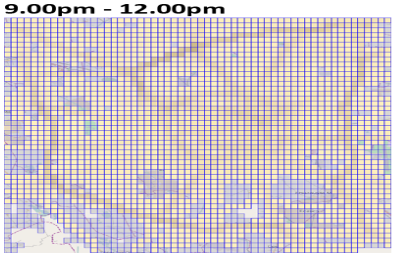
3.00pm - 6.00pm



6.00pm - 9.00pm



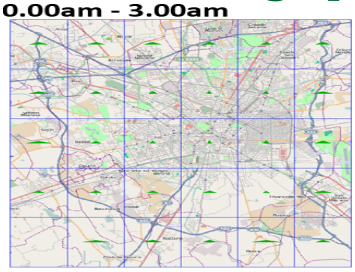
9.00pm - 12.00pm



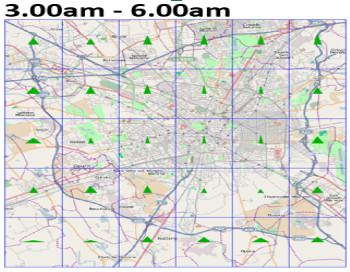


# Correlating speed and presence

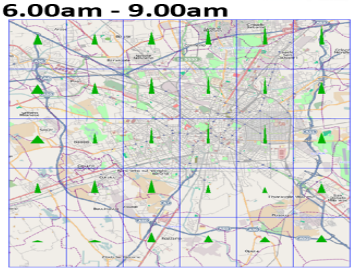
0.00am - 3.00am



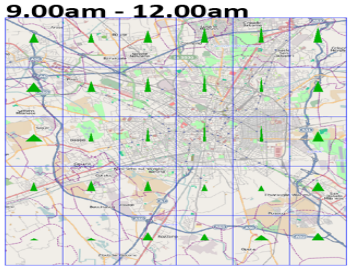
3.00am - 6.00am



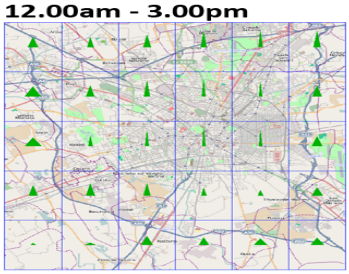
6.00am - 9.00am



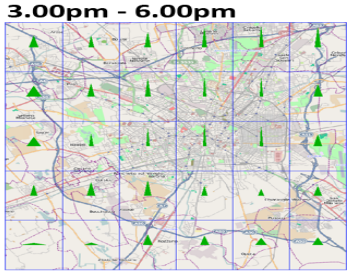
9.00am - 12.00am



12.00am - 3.00pm



3.00pm - 6.00pm



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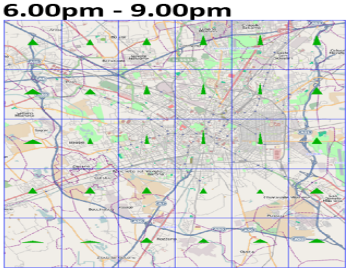

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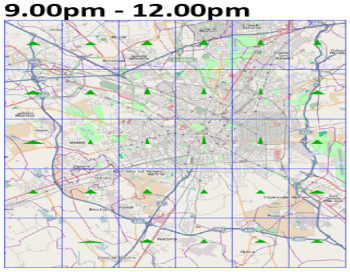
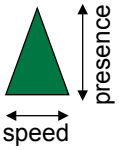




# Conclusions on Part I

- (Explorative) OLAP analysis over mobility data is a key tool for urban planning, etc.

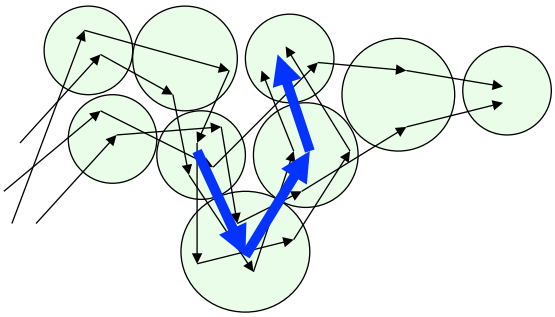
- Research challenges
  - Take network constraints into consideration
    - e.g. grid vs. graph (road network) partitioning at the Space dimension
  - Support "semantic trajectories" → semantic trajectory warehouses

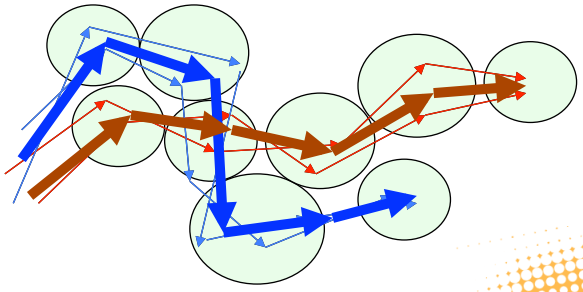


# part II: KDD

# KDD process over mobility data

- Knowledge discovery from mobility data
  - "*the opportunity to discover, from the **digital traces** of human activity, the **knowledge** that makes us comprehend timely and precisely the way we live, the way we use our time and our land*"
    [Giannotti & Pedreschi, 2008] [Giannotti et al. 2008]

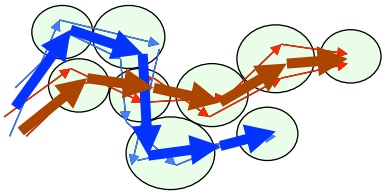




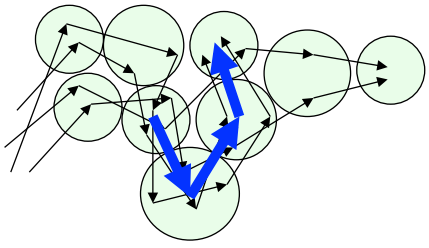


# Examples of mobility data mining

- **Trajectory clustering**
  - Cluster trajectories w.r.t. similarity
    - For each cluster, find its 'centroid' or 'representative'
  - Discover moving clusters (flocks), outliers, etc.



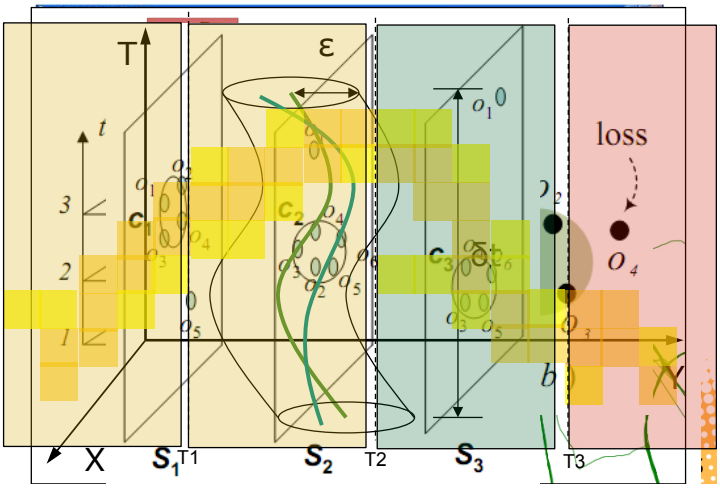
- **Frequent pattern mining**
  - Identify 'frequent' or 'popular' patterns
  - Discover hot spots, hot paths, etc.



- **Trajectory classification**
  - Assign trajectories to predefined classes
  - Find rules that may predict future behavior of moving objects
- **Trajectory sampling**
  - Out of the full population, select some representatives

# Applications of mobility data mining

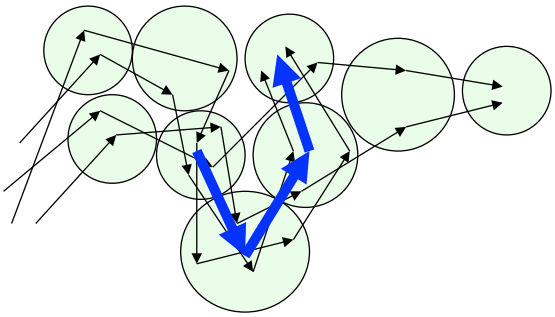
- Exploiting on “mobility patterns”
  - **Hot-spots** (popular places) [Giannotti et al. 2007]
  - **T-Patterns** [Giannotti et al. 2007]
  - **Hot motion paths** [Sacharidis et al. 2008]
  - **Typical trajectories** [Lee et al. 2007]
  - **Moving clusters** [Kalnis et al. 2005]
  - **Flocks & Leaders** [Benkert et al. 2008]
  - **Convoys** [Jeung et al. 2008]
  - **Centroid trajectories** [Pelekis et al. 2009-10]




# Frequent pattern mining

# "Frequent pattern mining" techniques

- Technical objectives:
  - Identify 'frequent' or 'popular' patterns
  - Discover hot spots, hot paths, etc.
- Related work:
  - Hot-spots (popular places) [Giannotti et al. 2007]
  - T-Patterns [Giannotti et al. 2007]
  - Hot motion paths [Sacharidis et al. 2008]





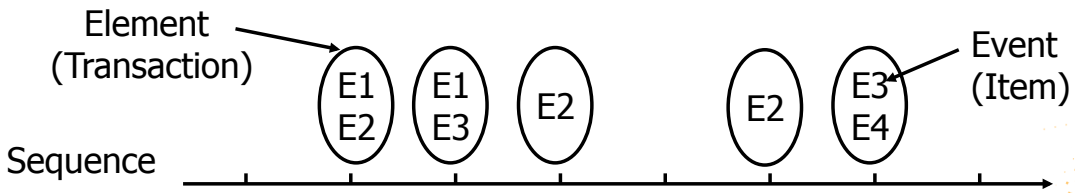
# A general definition

- The settings:
  - A dataset of entities $D = \{e_1, e_2, \ldots, e_N\}$
  - Each entity consists of a (temporal) sequence $e_i = \langle e_{i1}, \ldots, e_{iM} \rangle$ where $e_{ij}$ belongs to a set of items $I = \{I_1, \ldots, I_K\}$
- The objective goal:
  - Find sequences of items $\langle \ldots, I_i, I_j, \ldots \rangle$ which appear in this order frequently (i.e., at least d times) in the dataset. Such a sequence is called a **frequent pattern** in D

# Examples of Sequence Data

original slide from (Tan et al. 2004)

| Sequence Database | Sequence | Element (Transaction) | Event (Item) |
|---|---|---|---|
| Customer | Purchase history of a given customer | A set of items bought by a customer at time t | Books, diary products, CDs, etc |
| Web Data | Browsing activity of a particular Web visitor | A collection of files viewed by a Web visitor after a single mouse click | Home page, index page, contact info, etc |
| Event data | History of events generated by a given sensor | Events triggered by a sensor at time t | Types of alarms generated by sensors |
| Genome sequences | DNA sequence of a particular species | An element of the DNA sequence | Bases A,T,G,C |




# Sequential Pattern Mining: Example

original slide from (Tan et al. 2004)

| Object | Timestamp | Events |
|---|---|---|
| A | 1 | 1,2,4 |
| A | 2 | 2,3 |
| A | 3 | 5 |
| B | 1 | 1,2 |
| B | 2 | 2,3,4 |
| C | 1 | 1, 2 |
| C | 2 | 2,3,4 |
| C | 3 | 2,4,5 |
| D | 1 | 2 |
| D | 2 | 3, 4 |
| D | 3 | 4, 5 |
| E | 1 | 1, 3 |
| E | 2 | 2, 4, 5 |

*Minsup* = 50%

**Examples of Frequent Sub-sequences:**

| | |
|---|---|
| < {1,2} > | s=60% |
| < {2,3} > | s=60% |
| < {2,4}> | s=80% |
| < {3} {5}> | s=80% |
| < {1} {2} > | s=80% |
| < {2} {2} > | s=60% |
| < {1} {2,3} > | s=60% |
| < {2} {2,3} > | s=60% |
| < {1,2} {2,3} > | s=60% |

# Extracting Sequential Patterns

original slide from (Tan et al. 2004)

- Given n events: $i_1, i_2, i_3, \ldots, i_n$
- Candidate 1-subsequences:

  $\langle\{i_1\}\rangle, \langle\{i_2\}\rangle, \langle\{i_3\}\rangle, \ldots, \langle\{i_n\}\rangle$
- Candidate 2-subsequences:

  $\langle\{i_1, i_2\}\rangle, \langle\{i_1, i_3\}\rangle, \ldots, \langle\{i_1\}\ \{i_1\}\rangle, \langle\{i_1\}\ \{i_2\}\rangle, \ldots, \langle\{i_{n-1}\}\ \{i_n\}\rangle$
- Candidate 3-subsequences:

  $\langle\{i_1, i_2, i_3\}\rangle, \langle\{i_1, i_2, i_4\}\rangle, \ldots, \langle\{i_1, i_2\}\ \{i_1\}\rangle, \langle\{i_1, i_2\}\ \{i_2\}\rangle, \ldots,$

  $\langle\{i_1\}\ \{i_1, i_2\}\rangle, \langle\{i_1\}\ \{i_1, i_3\}\rangle, \ldots, \langle\{i_1\}\ \{i_1\}\ \{i_1\}\rangle, \langle\{i_1\}\ \{i_1\}\ \{i_2\}\rangle, \ldots$
- … by appropriately pruning at each step! (**A-priori style of thinking**)

# What is the "A-priori style of thinking"?

original slide from (Tan et al. 2004)

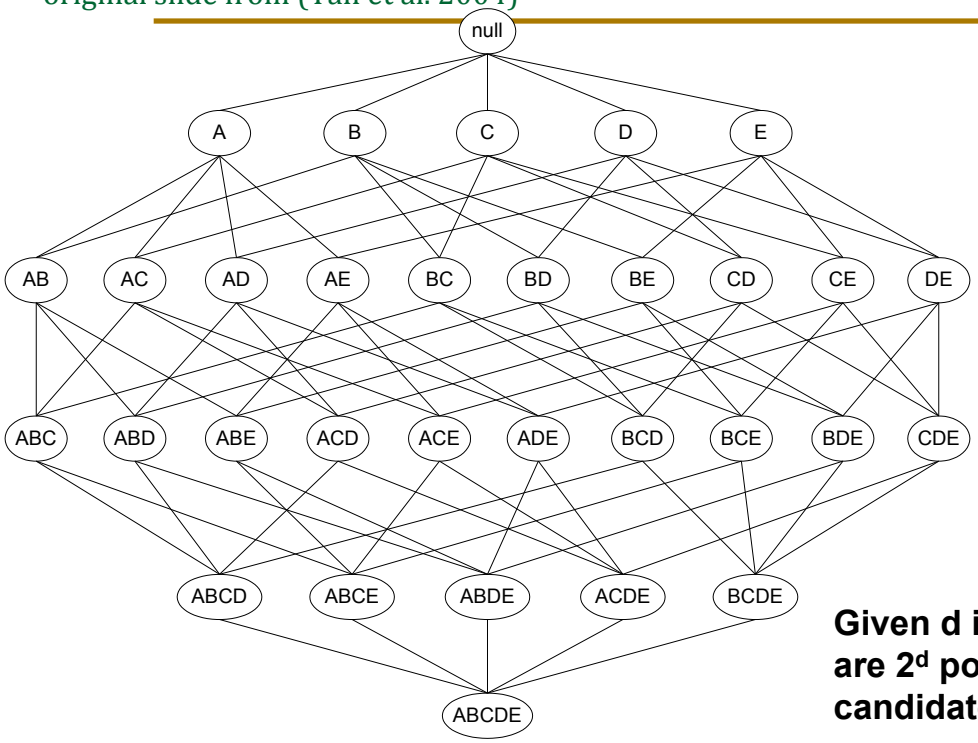
- **Itemset**: A collection of one or more items
  - Example: {Milk, Bread, Diaper}
- **k-itemset**: An itemset that contains k items
- **Support**: Fraction of transactions that contain an itemset
  - e.g. s({Milk, Bread, Diaper}) = 2/5

| *TID* | *Items* |
|---|---|
| 1 | Bread, Milk |
| 2 | Bread, Diaper, Beer, Eggs |
| 3 | Milk, Diaper, Beer, Coke |
| 4 | Bread, Milk, Diaper, Beer |
| 5 | Bread, Milk, Diaper, Coke |

- **Frequent Itemset**:
  - An itemset whose support is greater than or equal to a minsup threshold
- **Frequent Itemset Generation**
  - Generate all itemsets whose support ≥ minsup
  - Computationally expensive!

# Frequent Itemset Generation

original slide from (Tan et al. 2004)




**Given d items, there are $2^d$ possible candidate itemsets**

# Reducing Number of Candidates

original slide from (Tan et al. 2004)

- Apriori principle:
  - **If an itemset is frequent, then all of its subsets must also be frequent**

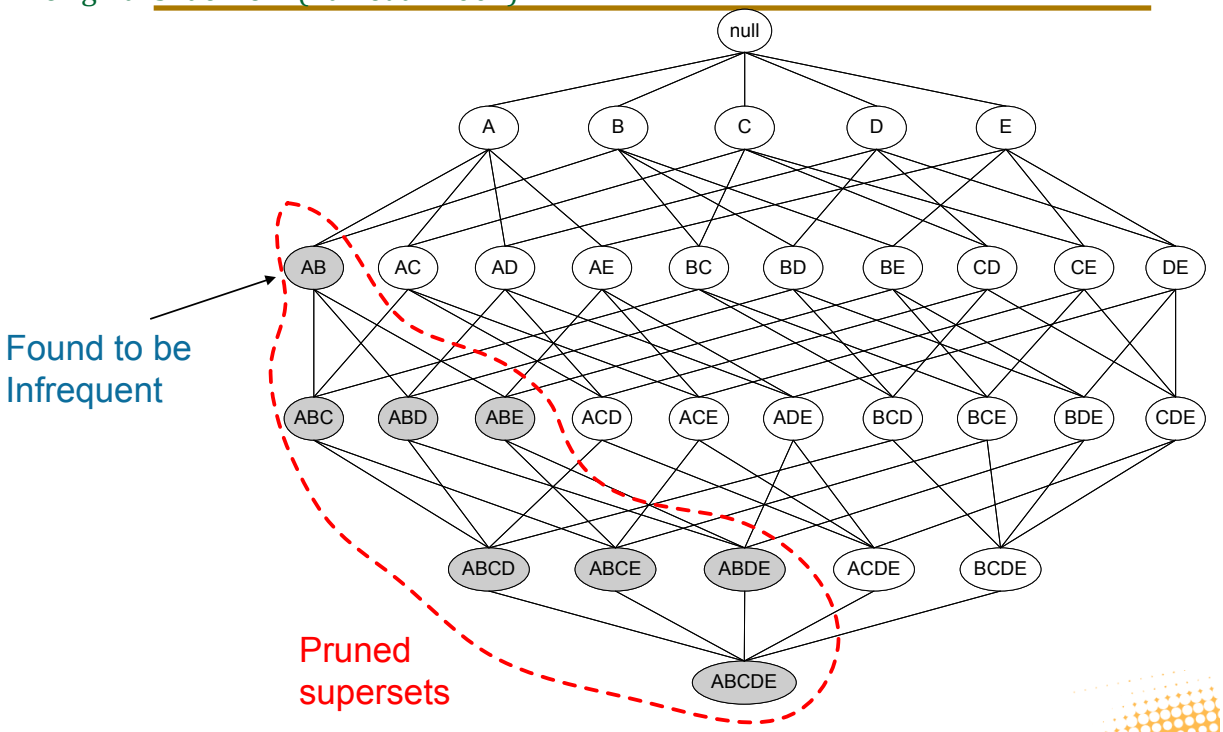
- Apriori principle holds due to the following property of the support measure:

$$\forall X, Y : (X \subseteq Y) \Rightarrow s(X) \geq s(Y)$$

  - Support of an itemset never exceeds the support of its subsets
  - This is known as the anti-monotone property of support

# Illustrating Apriori Principle

original slide from (Tan et al. 2004)




# Illustrating Apriori Principle

original slide from (Tan et al. 2004)

| Item | Count |
|---|---|
| **Bread** | **4** |
| **Coke** | **2** |
| **Milk** | **4** |
| **Beer** | **3** |
| **Diaper** | **4** |
| **Eggs** | **1** |

Items (1-itemsets)

| Itemset | Count |
|---|---|
| **{Bread,Milk}** | **3** |
| **{Bread,Beer}** | **2** |
| **{Bread,Diaper}** | **3** |
| **{Milk,Beer}** | **2** |
| **{Milk,Diaper}** | **3** |
| **{Beer,Diaper}** | **3** |

Pairs (2-itemsets)

(No need to generate candidates involving Coke or Eggs)

Minimum Support = 3

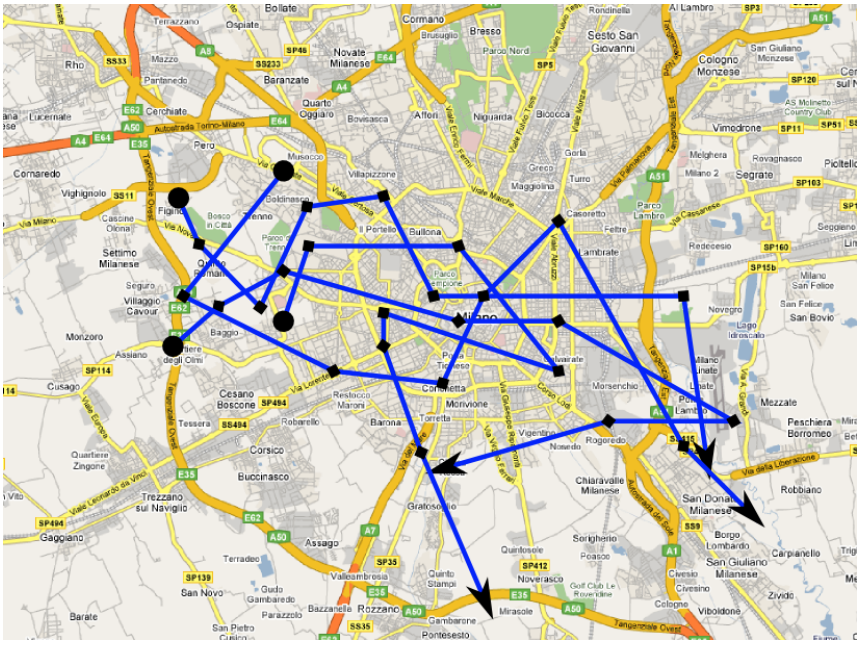
Triplets (3-itemsets)

| Itemset | Count |
|---|---|
| **{Bread,Milk,Diaper}** | **3** |

If every subset is considered,
$^{6}C1 + {}^{6}C2 + {}^{6}C3 = 41$
With support-based pruning,
$6 + 6 + 1 = 13$

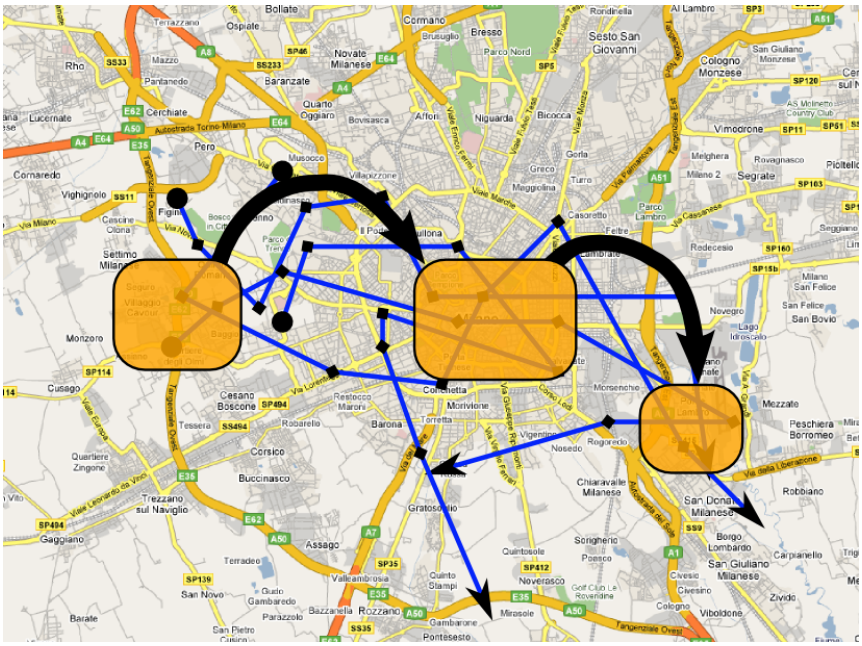
# Back to mobility data…

- What is a frequent pattern for trajectories?



# T-patterns

- [Giannotti et al. 2007] **T-pattern** is a sequence of visited regions, **frequently** visited in the **specified order** with **similar transition times**



# T-Pattern discovery

Input:
Trajectory
Dataset

Output: T-Patterns



Intermediate result:
Regions of Interest



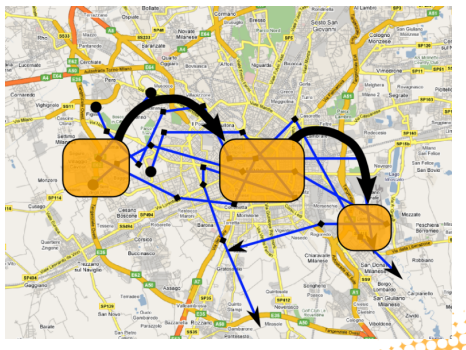
# T-Pattern definitions

- A **Trajectory Pattern** (T-pattern) is a pair (**s**, $\alpha$):
  - **s** = $<(x_0,y_0),\ldots,(x_k,y_k)>$ is a sequence of k+1 point locations
  - $\alpha = <\alpha_1,\ldots,\alpha_k>$ are the respective transition times (*annotations*)

  also written as:

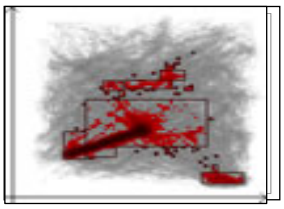
$$(x_0, y_0) \xrightarrow{\alpha_1} (x_1, y_1) \xrightarrow{\alpha_2} \cdots \xrightarrow{\alpha_k} (x_k, y_k)$$

- A T-pattern $T_p$ **occurs** in a trajectory T if T contains a sub-sequence S, such that:
  - *spatial closeness*
    - each point in $T_p$ is **close** to a point in S
  - *temporal closeness*
    - transition times in $T_p$ are **similar** to those in S

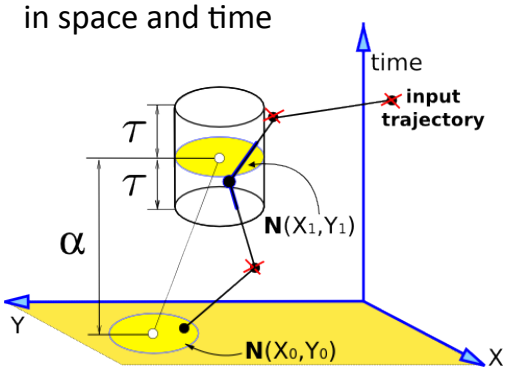


# T-Pattern discovery in 3-steps

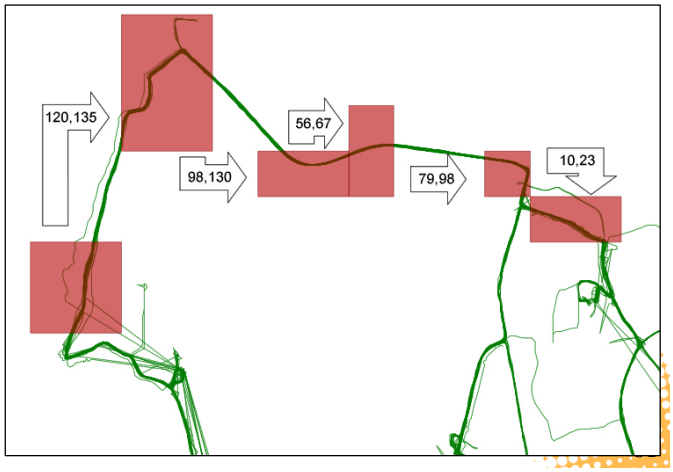
Step 1- Find Regions of Interest



Step 2- Find similar Trajectories in space and time



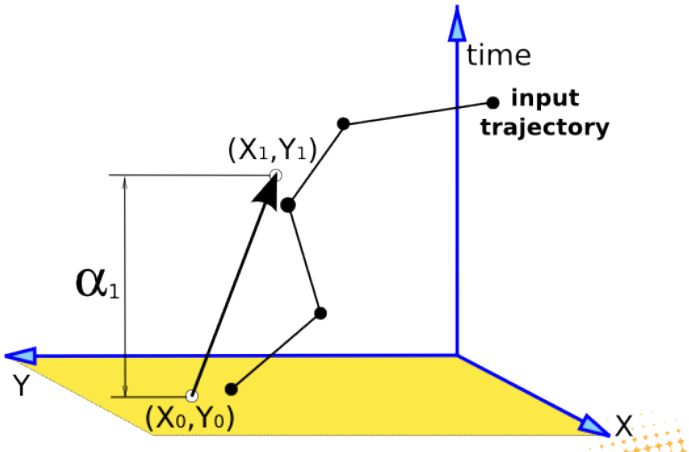

Step 3- Extract patterns with high support




# T-Pattern: *approximate* occurrence

- Two points are close to each other if one falls within a **spatial neighborhood N()** of the other
- Two transition times are similar to each other if their **temporal difference is ≤ τ**
- Example:

$$(x_0, y_0) \xrightarrow{\alpha_1} (x_1, y_1)$$



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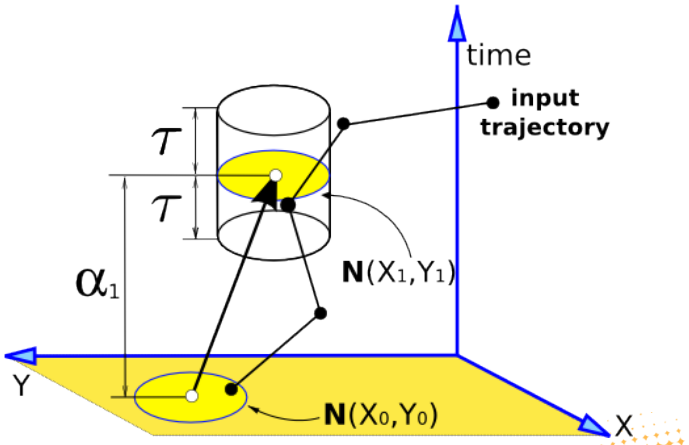
- Two transition times are similar to each other if their **temporal difference is ≤ τ**
- Example:

$$(x_0, y_0) \xrightarrow{\alpha_1} (x_1, y_1)$$

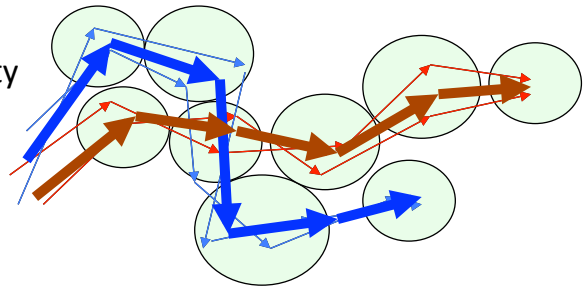





# Trajectory clustering

# "Trajectory clustering" techniques

- Technical objectives:
  - Cluster trajectories w.r.t. similarity
    - For each cluster, find its 'centroid' or 'representative'
  - Discover moving clusters (flocks), outliers, etc.



- Related work:
  - Moving clusters [Kalnis et al. 2005]
  - Typical [Lee et al. 2007] vs. Centroid trajectories [Pelekis et al. 2009]
  - Flocks & Leaders [Benkert et al. 2008]; Convoys [Jeung et al. 2008]

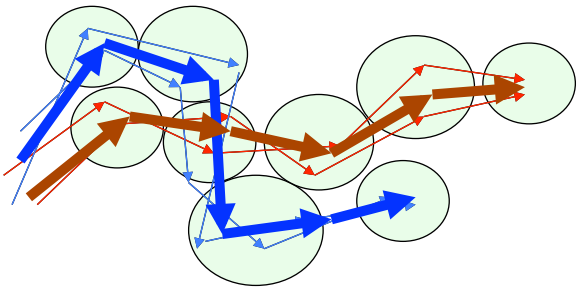


# A general definition

- The settings:
  - A dataset of entities $D = \{e_1, e_2, \ldots, e_N\}$
  - For each pair of entities, a distance $Dist(e_{ij})$ can be measured (hence, a NxN distance matrix is potentially formed)
    - (hopefully) the distance measure $Dist(e_{ij})$ should be a **metric**.
- The objective goal:
  - Partition entities of D into K groups (**clusters**), $G_1, \ldots, G_K$ with the following properties:
    - $\cup G_i = D$, $G_i \cap G_j = \varnothing$
    - The intra-cluster (inter-cluster) distance between entities is minimized (maximized, resp.), as better as possible

# Back to mobility data…

- Questions:
  - Which distance between trajectories? How do we define intra- and inter-cluster distances?
  - Which kind of clustering?
    - Partitioning (like K-means)? Density-based (like DBSCAN or OPTICS)?
  - How does a cluster 'centroid' look like in our case?
    - A "trajectory" representing the trajectories of a cluster, as better as possible



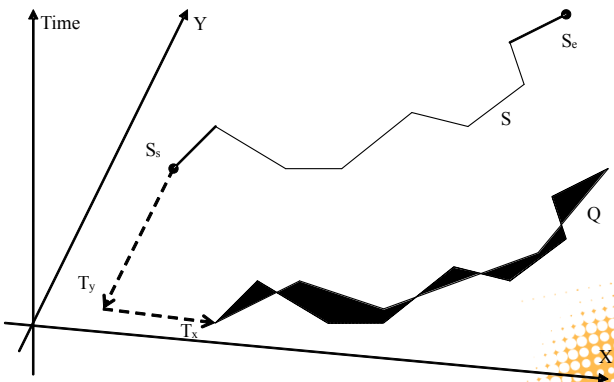
# Which distance?

- A possible solution: average Euclidean distance between (sub-) trajectories

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

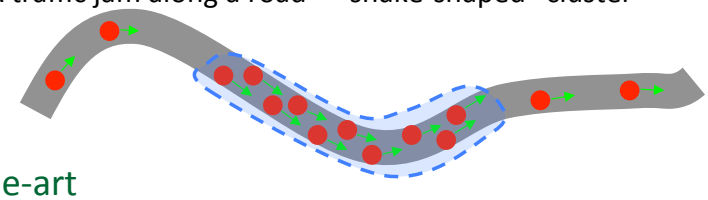
**distance between moving objects τ1 and τ2 at time *t***

- "Synchronized" behaviour distance
  - Similar trajectories ➔ in similar places at similar timestamps
- Good news: it is a **metric**
  - Result: efficient indexing, e.g. [Frentzos et al. 2007]



# Which kind of clustering?

- General requirements:
  - Tolerance to noise; Low computational cost; Applicability to complex, possibly non-vectorial data; Non-spherical clusters; etc.
    - E.g.: A traffic jam along a road = “snake-shaped” cluster

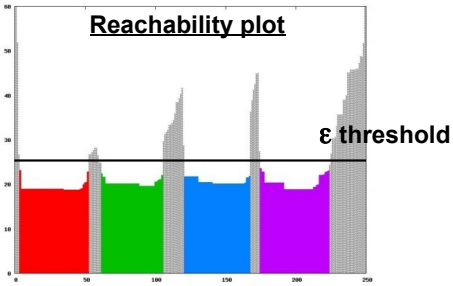


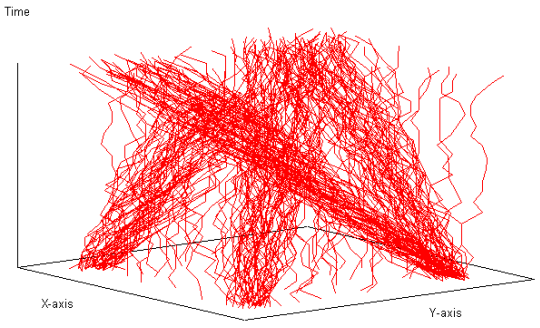
- State-of-the-art
  - Density-based clustering: **T-OPTICS** [Nanni & Pedreschi, 2006]
  - **CenTR-I-FCM** [Pelekis et al. 2009, 2011]

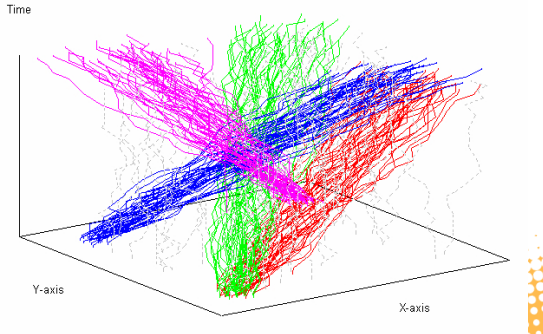


# T-OPTICS

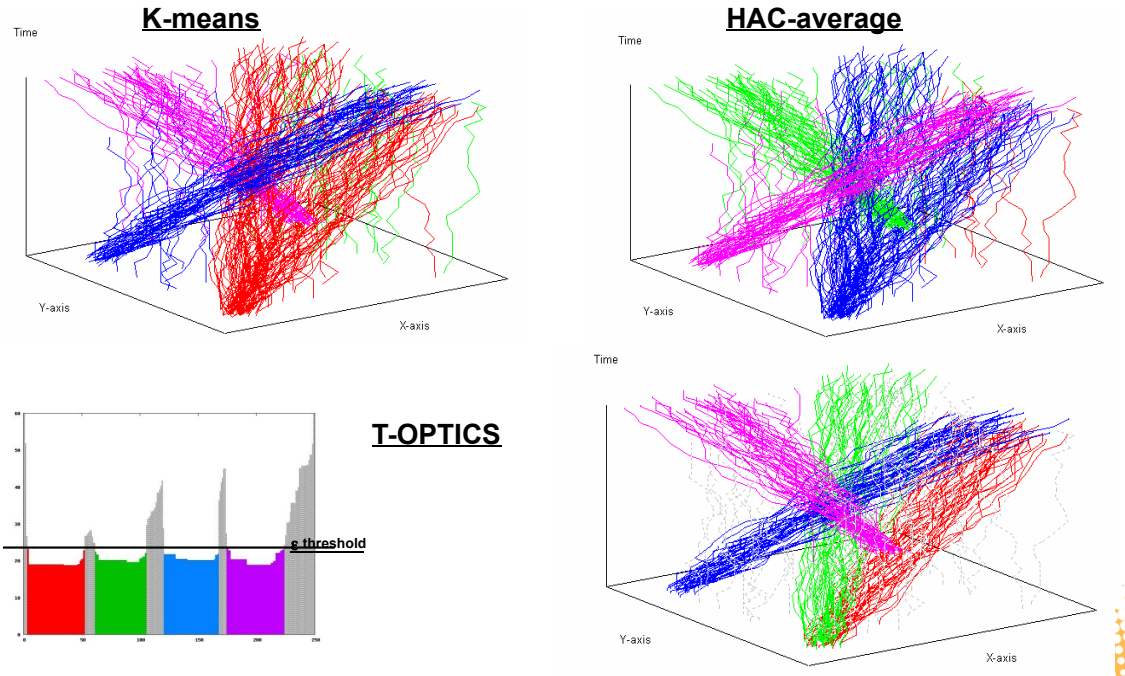
- Builds upon OPTICS
- Keywords:
  - distance, core trajectories, reachability
- Reachability plot (valleys and hills)
  - Valleys → clusters !!



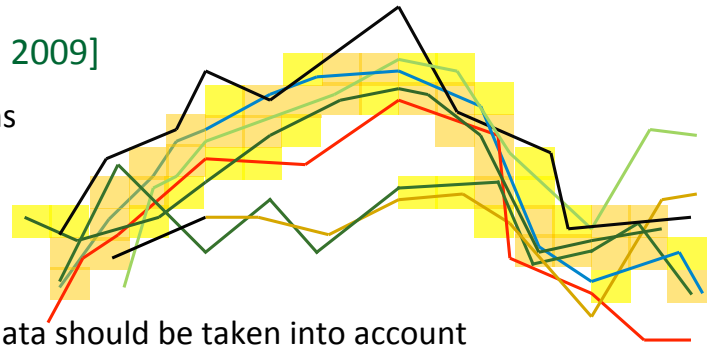



# T-OPTICS vs. HAC & K-means






# CenTR-I-FCM: Clustering under uncertainty



- CenTR-I-FCM [Pelekis et al. 2009]
  - Builds upon Fuzzy-C-Means (a variation of K-means for uncertain data)
- Motivation:
  - uncertainty of trajectory data should be taken into account
- Three phases:
  - Step 1: **mapping** of trajectories in an intuitionistic fuzzy vector space
  - Step 2: **discovering the centroid** of a bundle of trajectories (algorithm CenTra)
  - Step 3: **clustering** trajectories under uncertainty (algorithm CenTR-I-FCM)

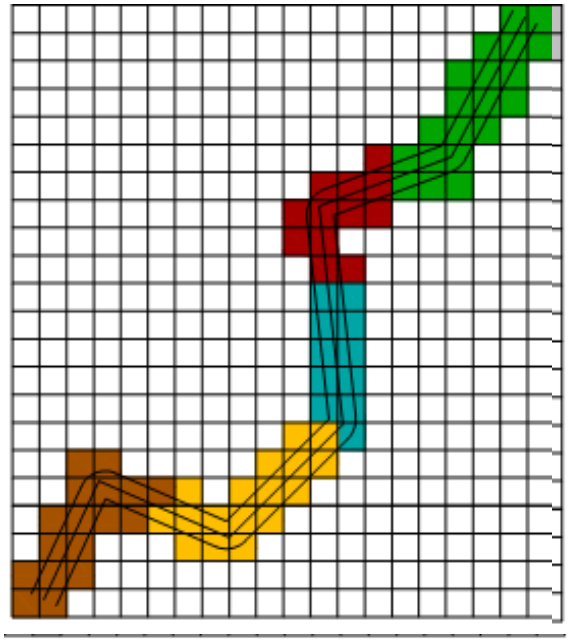
# Step 1: trajectories as intuitionistic fuzzy vectors

- Settings:
  - a grid partitioning of space
  - a target dimension $p$ << # timestamps
- **Approximate trajectory**
  - a sequence of $p$ regions (i.e., sets of cells crossed by the trajectory)

$$\overline{T}_i = \langle r_{i,1}, \ldots, r_{i,p} \rangle$$

- **Uncertain Trajectory** (UnTra)
  - the $\varepsilon$-buffer of the approximate trajectory

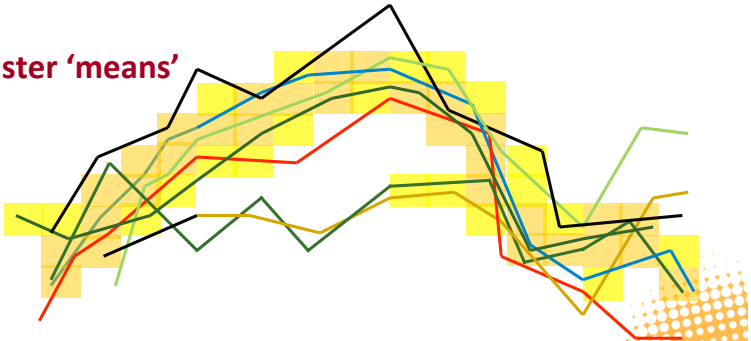
$$UnTra(\overline{T}_i) = \langle ur_{i,1}, \ldots, ur_{i,p} \rangle$$



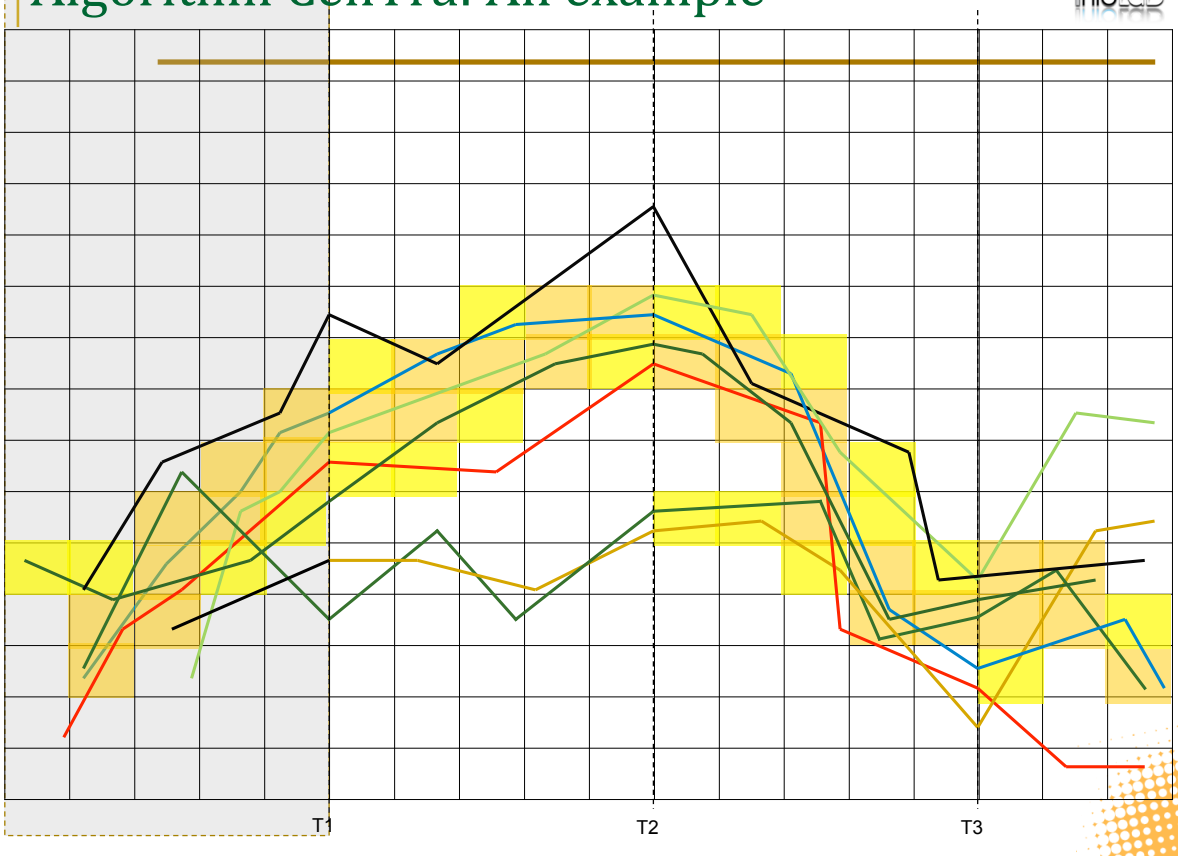


# Steps 2-3: clustering using 'centroids'

- Step 2 – discover the **centroid** of a bundle of trajectories
  - adopt a local similarity function to identify common sub-trajectories (concurrent existence in space-time), and
  - follow a region growing approach according to density
- Step 3 - clustering
  - adopt Fuzzy-C-Means (FCM), an extension of k-means for clustering uncertain data
  - **using CenTRa as the cluster 'means'**

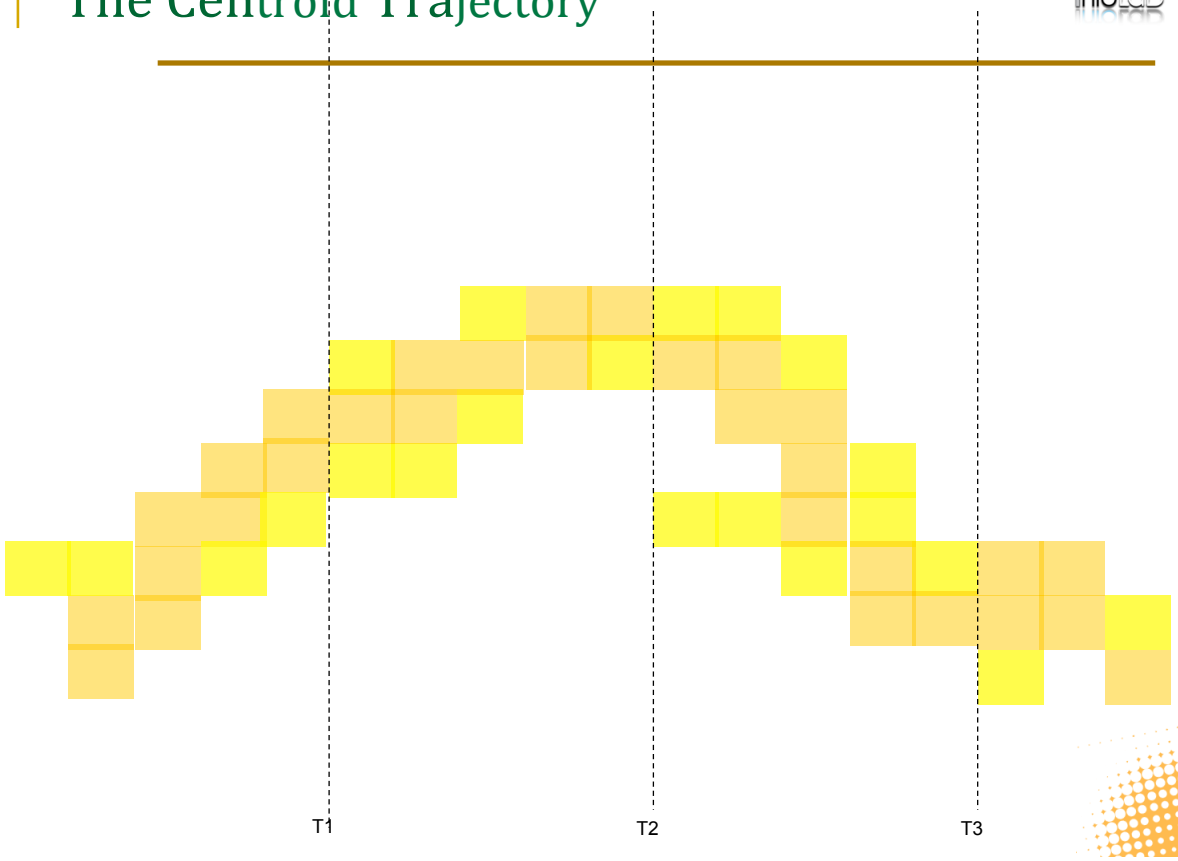


# Algorithm CenTra: An example





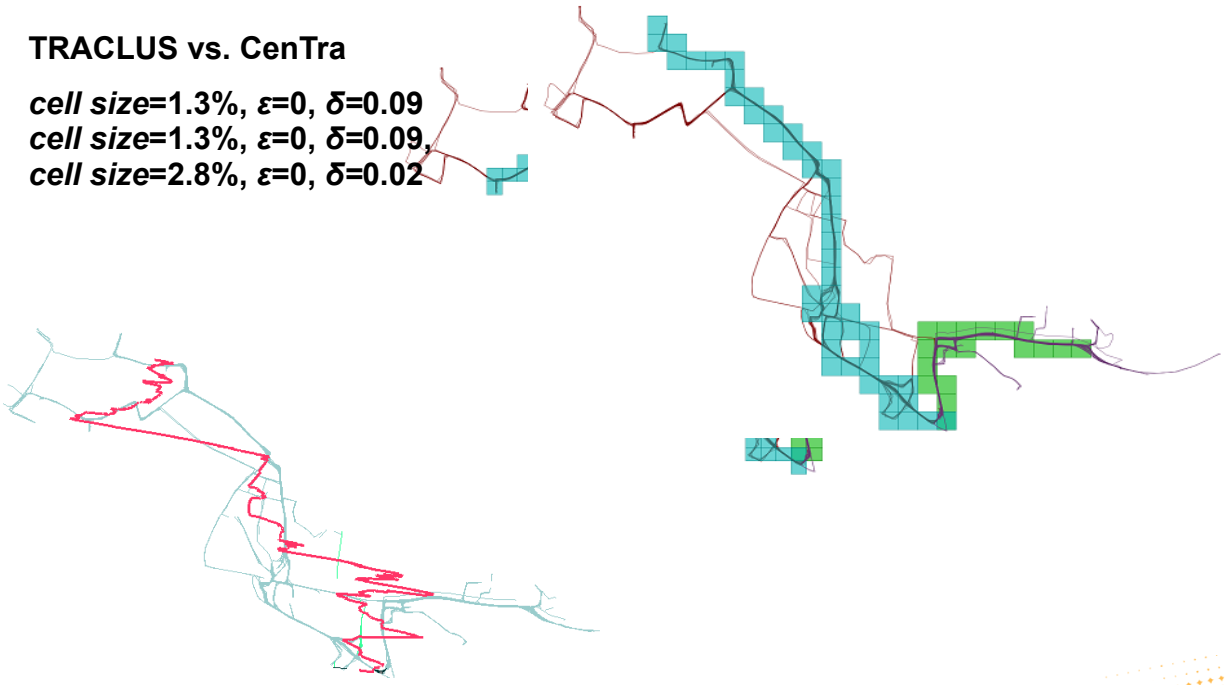

# The Centroid Trajectory



# Quality of centroid

**TRACLUS vs. CenTra**

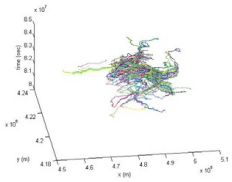
***cell size*=1.3%, *ε*=0, *δ*=0.09**
***cell size*=1.3%, *ε*=0, *δ*=0.09,**
***cell size*=2.8%, *ε*=0, *δ*=0.02**

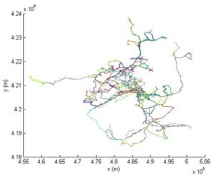




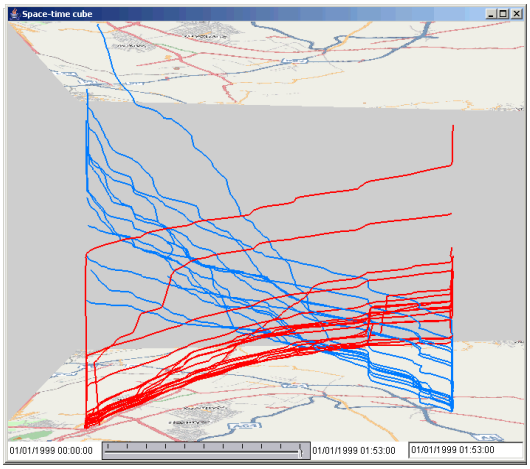
# CenTR-I-FCM on work…

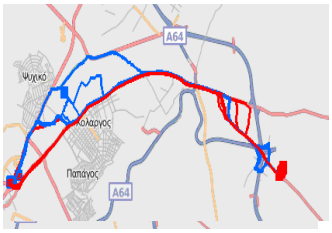
- Settings
  - Dataset: 'Athens trucks' MOD (www.rtreeportal.org)
    - 50 trucks, 1100 trajectories, 112,300 position records
  - Use CommonGIS [Andrienko et al., 2007] to identify real clusters





**"Round trips" clusters**

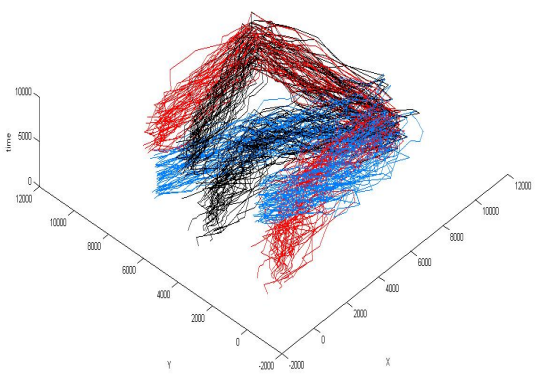


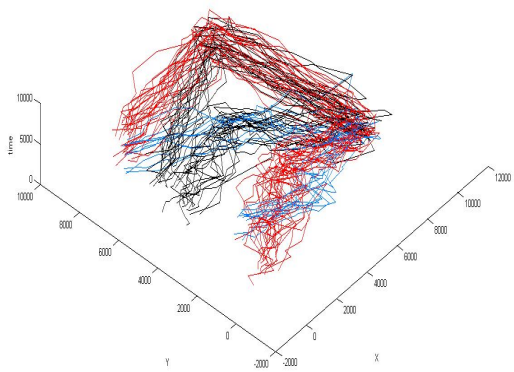



# Trajectory sampling

## Sampling trajectory datasets

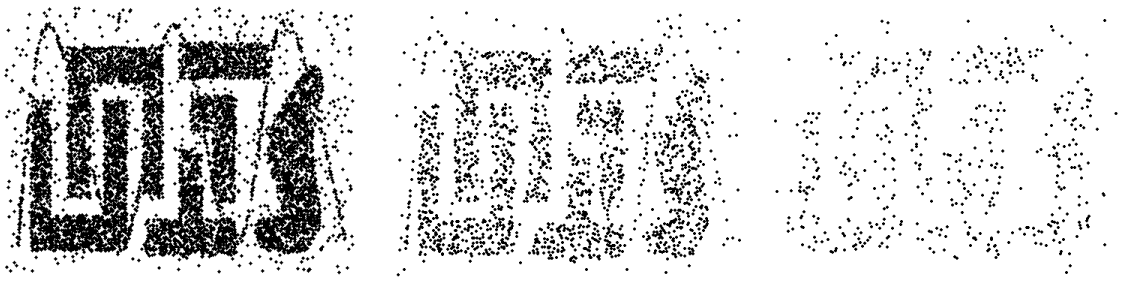
- Can we get the gist of a real large MOD by visualizing it? Can we do this automatically?
- If yes, we can
  - extrapolate the query results from queries in the sampled MOD
  - discover mobility patterns working with a “representative” subset



# A general definition

- **Sampling** is the main technique employed for data selection.
  - It is often used for both the preliminary investigation of the data and the final data analysis.
  - Statisticians sample because obtaining the entire set of data of interest is too expensive or time consuming.



**8000 points** **2000 Points** **500 Points**

# A general definition (cont.)

- The key principle for effective sampling is the following:
  - using a sample will work almost as well as using the entire data sets, if the sample is representative
  - A sample is representative if it has approximately the same property (of interest) as the original set of data

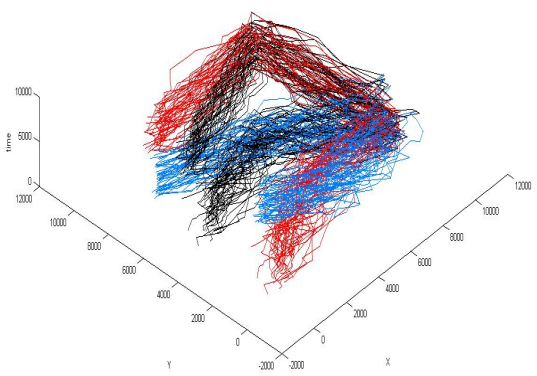
- As such, sampling is also used in data mining because **processing the entire set of data of interest is too expensive or time consuming.**

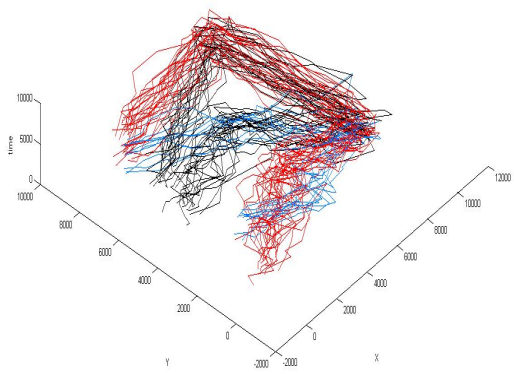
# Types of sampling

- Simple Random Sampling
  - There is an equal probability of selecting any particular item
- Stratified sampling
  - Split the data into several partitions; then draw random samples from each partition
- Sampling with vs. without replacement
  - As each item is selected, it remains at (vs. it is removed from) the population
    - In sampling with replacement, the same object can be picked up more than once!

# Back to mobility data…

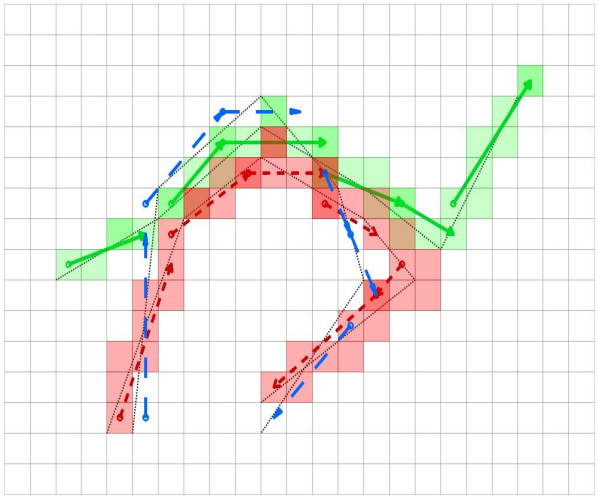
- How can we select some out of the entire population of trajectories?
- Recall that …
  - "A sample is representative if it has approximately the same property (of interest) as the original set of data"



# Vector representation of trajectories

- Settings (as before):
  - a grid partitioning of space
  - a target dimension $p$ << # timestamps
- **Approximate trajectory** (ApTra)
  - consists of $p$ "directed regions", which are pairs of
    - region (i.e., set of cells crossed by the trajectory) and
    - region's direction (defined wrt. its ending cells)

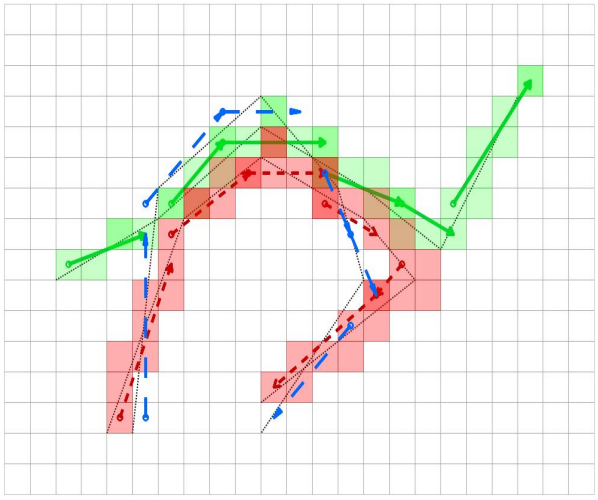


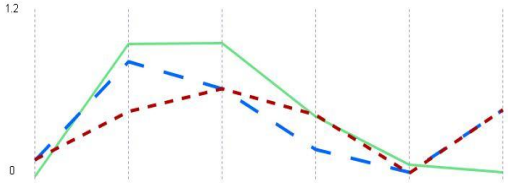
$$\overline{T}_i = <\left(r_{i,1}, \vec{d}_{i,1}\right), \ \ldots, \ \left(r_{i,p}, \vec{d}_{i,p}\right)>$$



# "Representative" trajectories

- "**Representativeness**" of a trajectory
  - the number of other trajectories that are **similar** to it
- Technically:
  - A **voting process** applied to each directed region $dr_{i,j}$
  - A directed region is voted by an ApTra in the dataset according to their distance
  - Thus, a 3rd value ("representative-ness") is attached to each directed region
- The result: **Representative trajectory** (ReTra)
  - a set of p triplets $\left(r_{i,j}, \vec{d}_{i,j}, v(dr_{i,j})\right)$





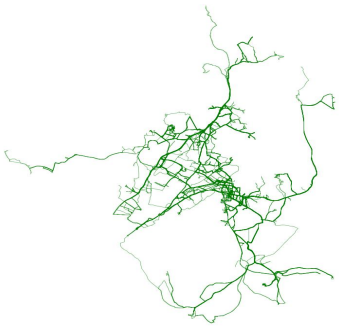
# T-Sampling problem formulation

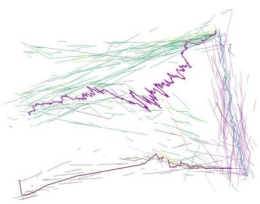
- For each sub-trajectory in a dataset D, we can calculate its trajectory representativeness descriptor Vi(D)
- **Motivation**: Selecting the top-voted sub-trajectories is not the best idea for making a sampling set !!
- Definition of the T-sampling problem:
  - Optimization problem: find an appropriate subset S of D, which maximizes the function SR(S): $SR(S) = \sum_{i=1}^{N} S_i \bullet V_i(D) \bullet (1 - V_i(S))$
    - Si is equal to 1 (0) when (sub-)trajectory Ti belongs (does not belong, resp.) to the sampling set.
  - **Meaning:** the number of trajectories in D that find their representatives in S is maximized

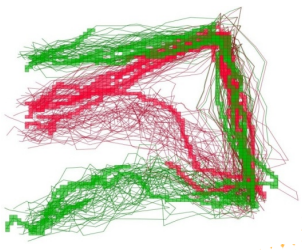


# T-sampling on work…

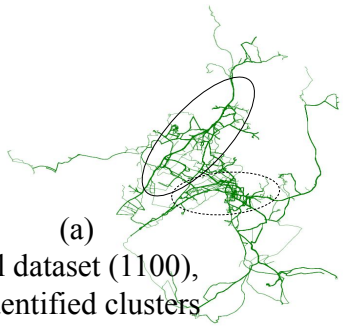
- How "good" is the sample produced by T-sampling?
- … where "good" means …
  - Can we visualize real-world datasets using only a subset?
  - Does the sample preserve the hidden mobility patterns?



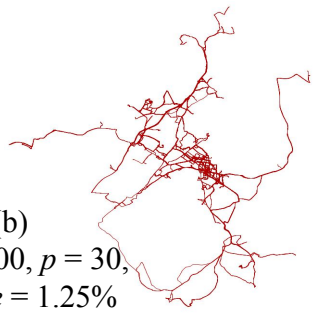




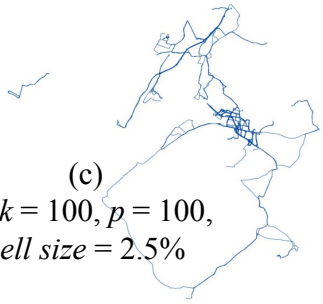
# T-sampling on work…



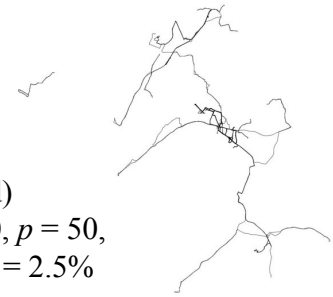
(a)
Full dataset (1100),
2 identified clusters



(b)
top$k$ = 200, $p$ = 30,
*cell size* = 1.25%



(c)
top$k$ = 100, $p$ = 100,
*cell size* = 2.5%

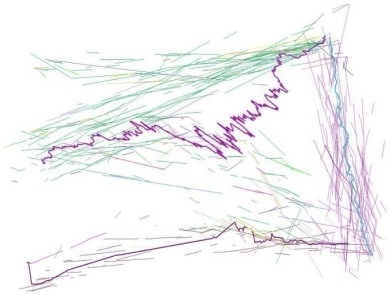


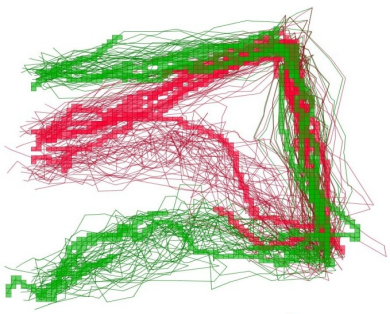
(d)
top$k$ = 40, $p$ = 50,
*cell size* = 2.5%



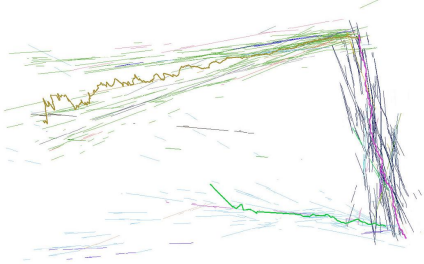
# T-sampling on work…

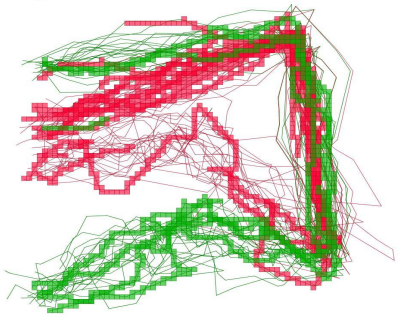
- Preservation of mobility patterns





**Before**



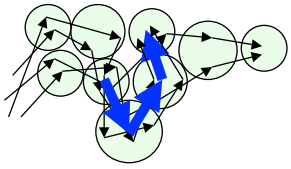


**After**
Sampling

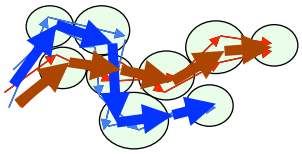
**TRACLUS** representatives [Lee et al. 2007] and **CenTra** centroids [Pelekis et al. 2009]

# Research challenges in mobility data mining

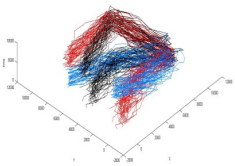
- Frequent pattern mining
  - What about a hierarchy of T-patterns, from more to less general? e.g.
    - coarser level: from north to downtown in 1 hour
    - finer level: from highway A to ring in 20 min.

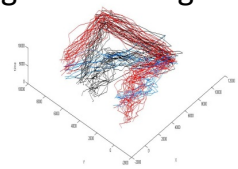


- Trajectory clustering
  - (as usual) find the optimal number ‘k’ of clusters
  - incremental clustering



- Trajectory sampling
  - Could samples be used for privacy-preserving data mining?







# Questions

# Reading list

(spatial, spatio-temporal and)

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