Spatial Data Mining - Introduction

SHEKHAR, S., CHAWLA, S. Spatial databases: a tour. Upper Saddle River, NJ: Prentice Hall, 2003.

Bogorny, V. and Shekhar S. *Tutorial on Spatial and Spatio-Temporal Data Mining* In: SBBD 2008. (http://www.inf.ufsc.br/~vania/tutorial.zip).

Spatial Databases

- Database that:
  - Stores spatial objects
  - Provides data types for spatial objects
  - Provides operations to manipulate spatial objects
  - Manipulates spatial objects just like other objects in the database

Spatial Databases

- Oracle Spatial
- IBM DB2 Spatial Extender
- Informix Spatial DataBlade
- MS SQL Server (with ESRI SDE)
- Geomedia on MS Access
- PostGIS / PostgreSQL

- TerraView (Spatial Data Visualization and Analysis)

Spatial Data

- Data which describe a location or a shape
  - e.g. House, Hospital, Road, River, Forests, Parks, Soil
- Is something that describes objects or phenomena that happen on the Earth and that have associated a geographic position

Three main characteristics describe a geographic object:

- Non-spatial attributes (what): describe either quantitatively or qualitatively a geographic entity.
  - These attributes may be treated by non-spatial databases;

- Spatial attribute (where): describe the spatial location and representation of the geographic object, considering the geometry and a coordinate system.
  - This aspect requires a specific data type not available in conventional DBMS;

- Spatial relationships (how): neighbourhood relationships (e.g. topology, distance).
  - Requires special operations that are not available in conventional DBMS;

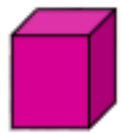
Spatial Representation: OBJECT

- Discrete objects (Features): well defined border/limit
  - 0-dimensional
    - representation: point
    - E.g.: school, hospital

  - Uni-dimensional
    - representation: line
    - E.g.: river, road

  - Bi-dimensional
    - representation: polygon
    - E.g.: state, city

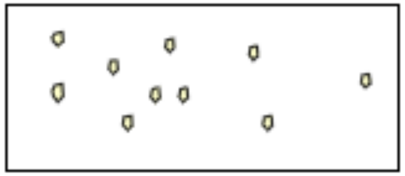
  - Tri-dimensional
    - representation: surface



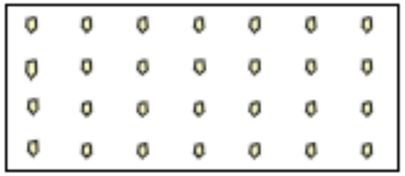
Spatial Representation: FIELD

Continuous Data

Irregular points (e.g. temperature)

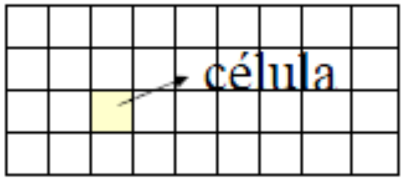


Regular Points

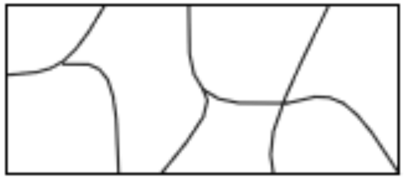


Isoline (e.g. relief)

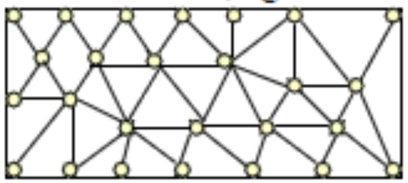
Grid (e.g. satellite image)



Adjacent polygons (e.g. soil)



Triangulated Network (e.g. the floor of a valley)



Geographic Data and Geographic Databases: an example

Street

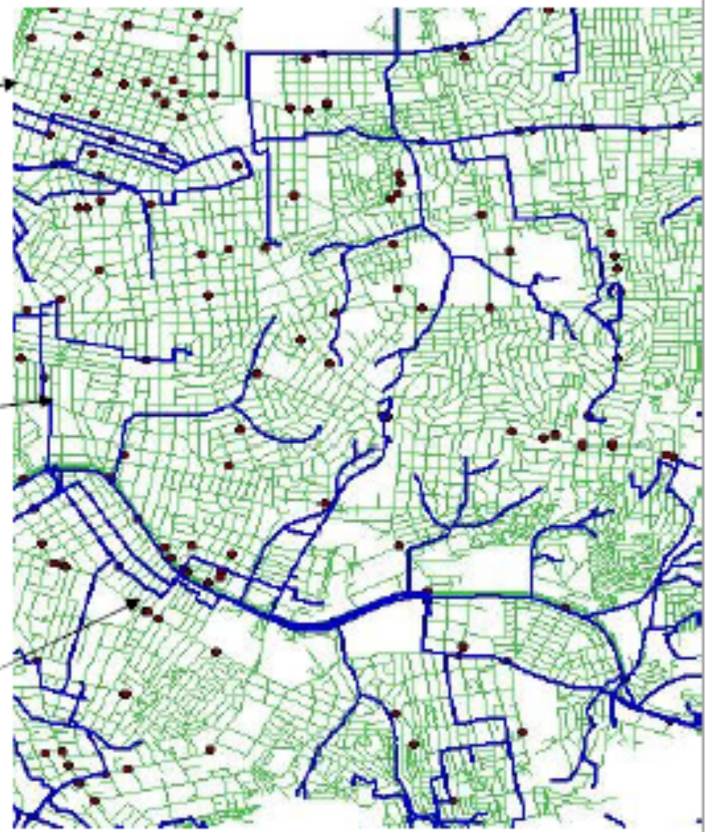
Gid	Name	Shape
1	Ijui	Multiline [(x1,y1),(x2,y2),..]
2	Lavras	Multiline [(x1,y1),(x2,y2),..]

WaterResource

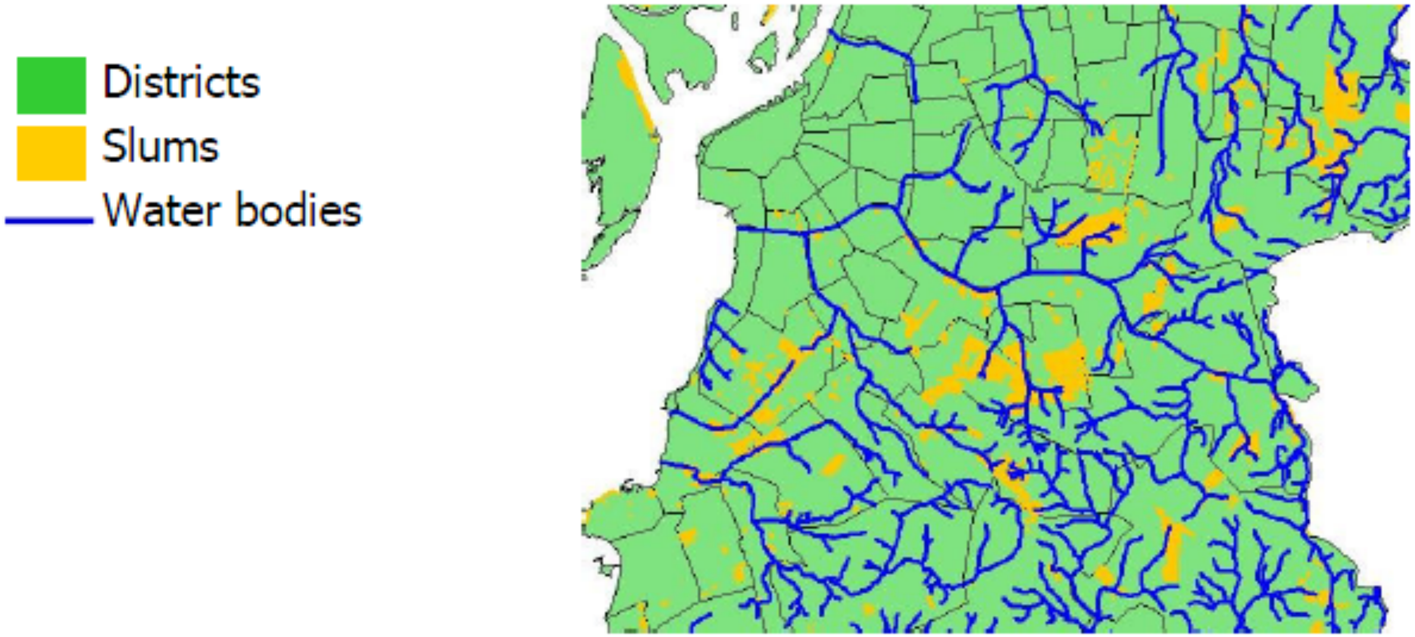
Gid	Name	Shape
1	Jacui	Multiline [(x1,y1),(x2,y2),..]
2	Guaiba	Multiline [(x1,y1),(x2,y2),..]
3	Uruguai	Multiline [(x1,y1),(x2,y2),..]

GasStation

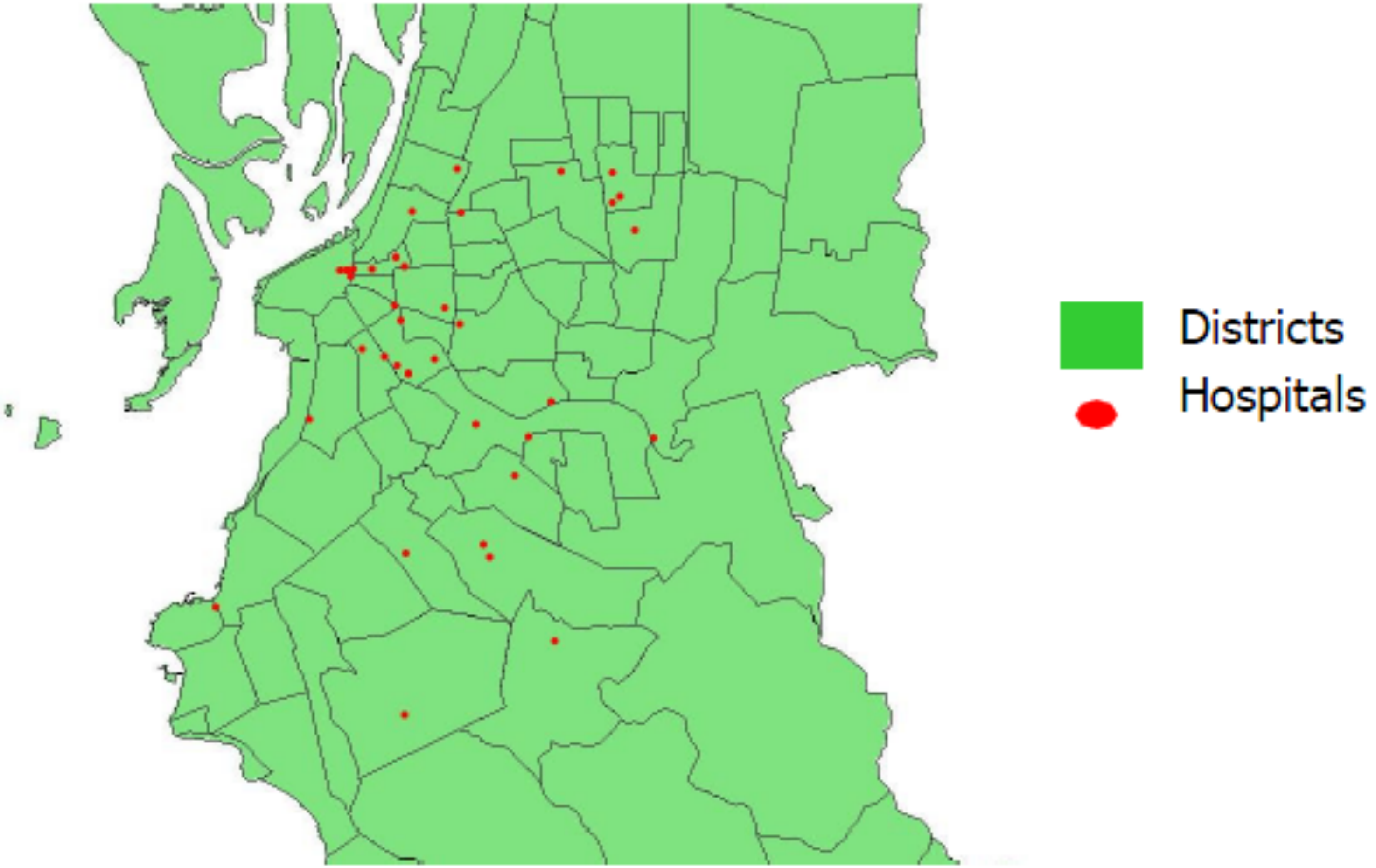
Gid	Name	VolDiesel	VolGas	Shape
1	BR	20000	85000	Point[(x1,y1)]
2	IPF	30000	95000	Point[(x1,y1)]
3	Esso	25000	120000	Point[(x1,y1)]



Example of Geographic Data

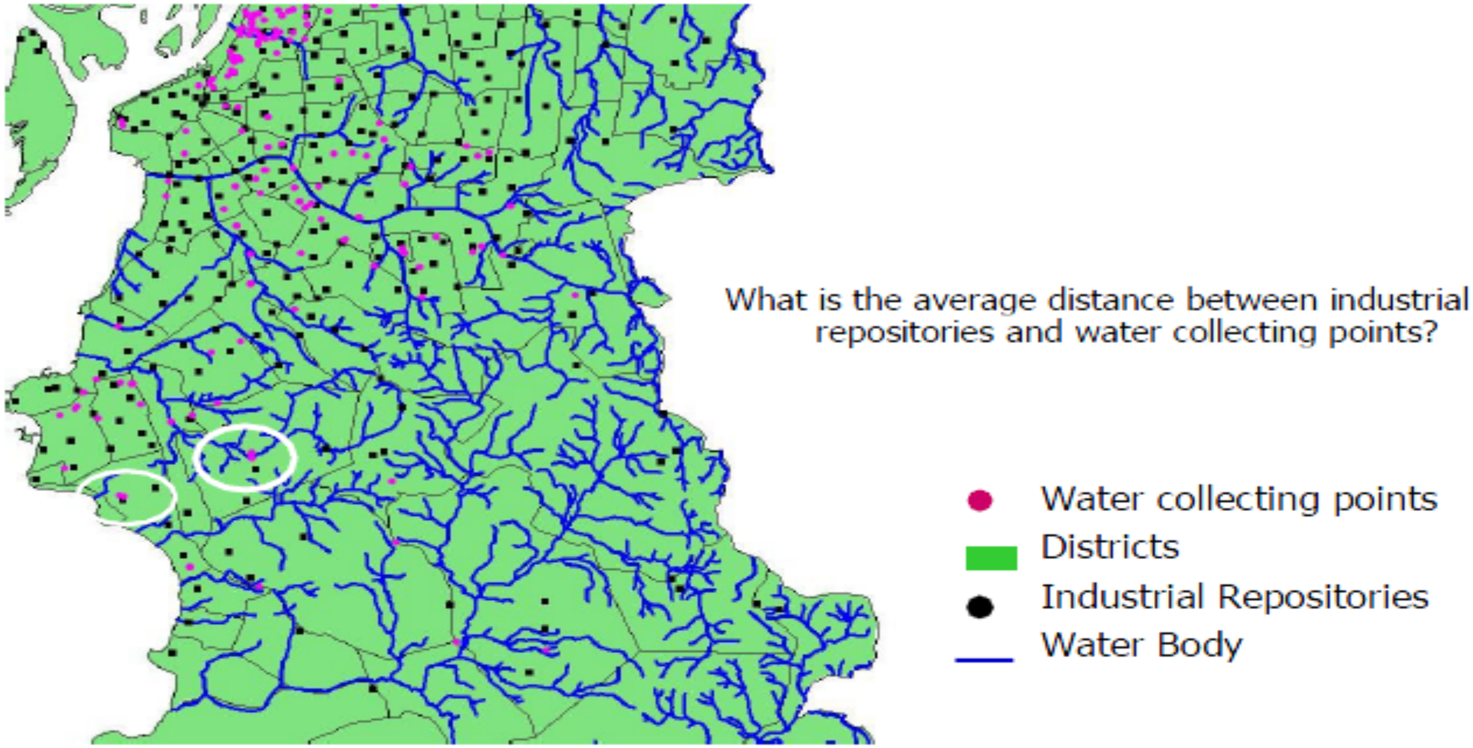


Example of Geographic Data

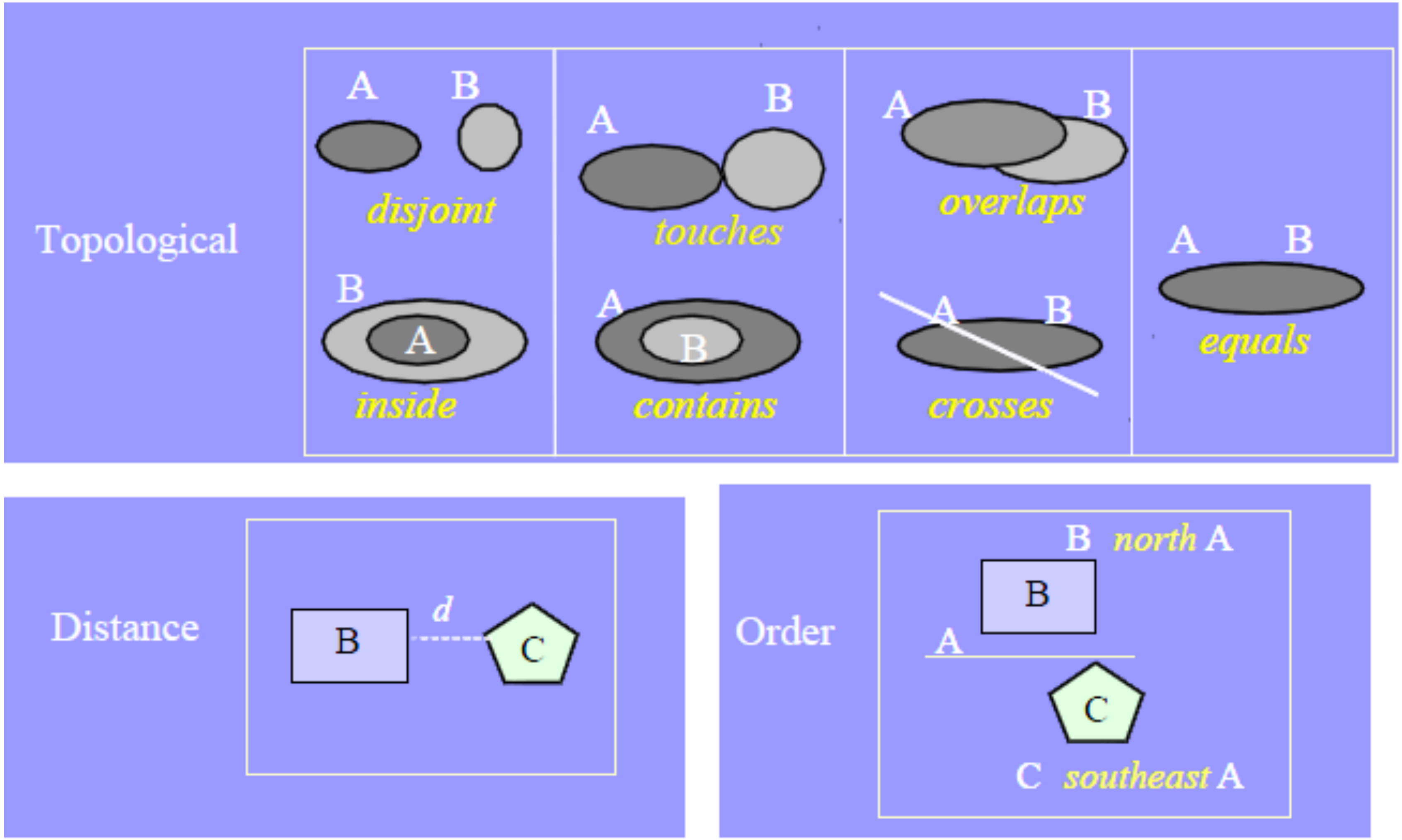


Spatial Relationships

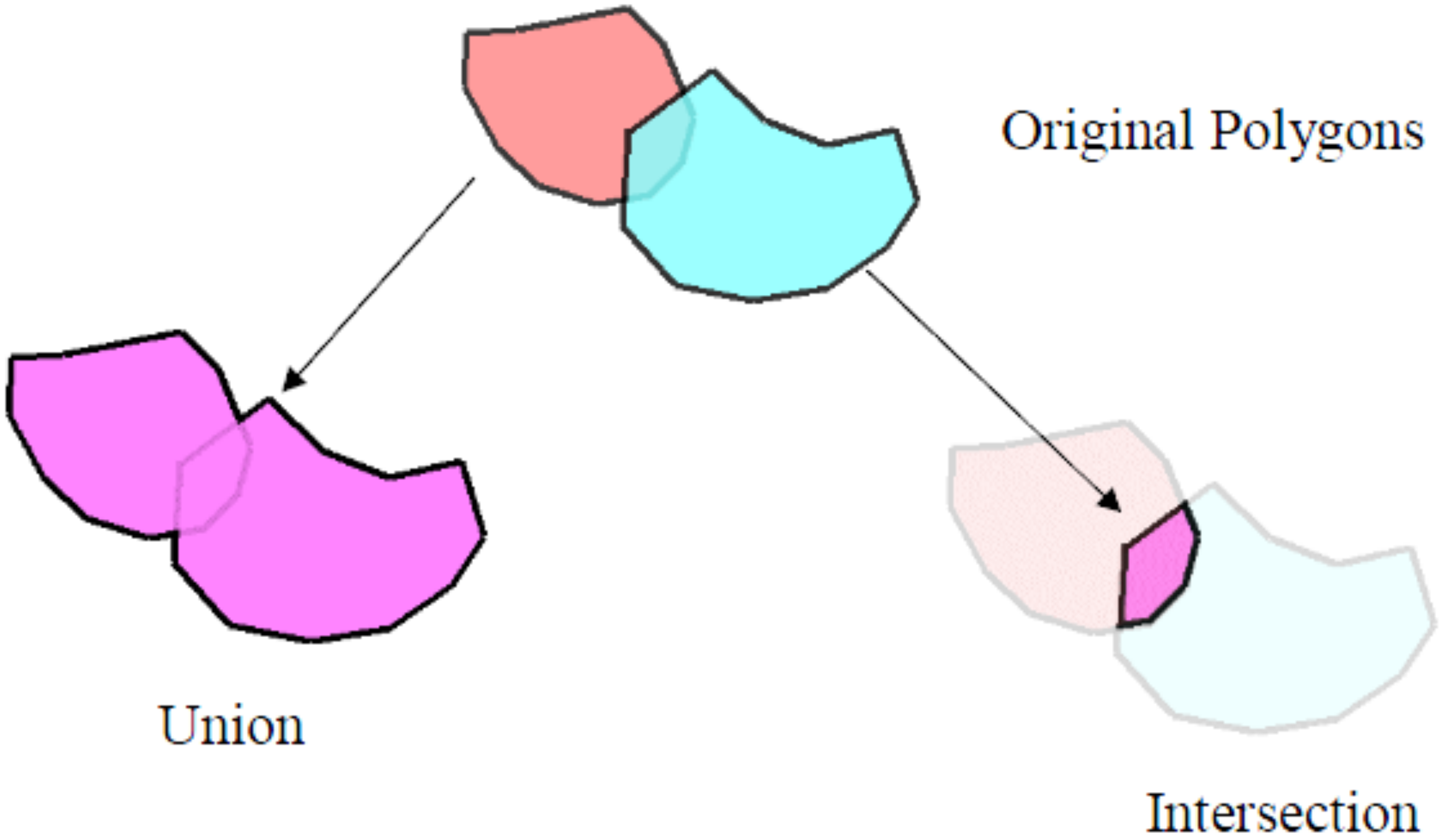
- Main characteristic which differs spatial data from non-spatial data
- Main aspect to be considered in SPATIAL DATA MINING



Spatial Relationships



Exemples of Spatial Operations



Examples of Spatial Operations

Rivers

Buffered Rivers

Advantages of Spatial Databases

- Spatial querying using SQL
  - SQL expressions to determine spatial relationships
    - distance
    - order
    - topology
  - SQL expressions to perform spatial operations
    - area
    - length
    - union
    - buffer

Spatial Query Language

- Spatial query language provides:
  - spatial data types, e.g. point, line, polygon, …
  - spatial operations, e.g. overlap, distance, buffer, …
  - example:

```
SELECT S.name
FROM State S
WHERE area (s.the_geom) > 300
```

- Standards
  - OGIS is a standard for spatial data types and operators

Spatial Query Example

Q1: Retrieve the rivers and countries that have the relationship "crosses".

Query

```
SELECT r.name, c.cntry_name
   FROM river r, country c
 WHERE crosses (r.the_geom,c.the_geom) = 'True'
```

Answer

```
        name                   |  cntry_name
-------------------------------+--------------
 Pembina                       | United States
 Pembina                       | Canada
 Rainy                         | United States
 Rainy                         | Canada
 Souris                        | United States
 Souris                        | Canada
 Red River of the North        | United States
 Red River of the North        | Canada
(8 rows)
```

Spatial Query Example

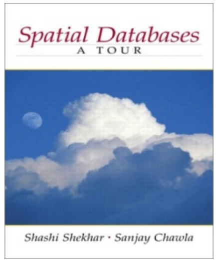
Q2: Retrieve the states adjacent to the state "Santa Catarina".

Query

```
SELECT s1.name as state_Neighbors
  FROM state s1, state s2
 WHERE touches(s1.the_geom, s2.the_geom)=TRUE
         and  s1.state_name=´Santa Catarina´;
```

Answer

```
State_Neighbors
--------------------
Rio Grande do Sul
Paraná
(2 rows)
```



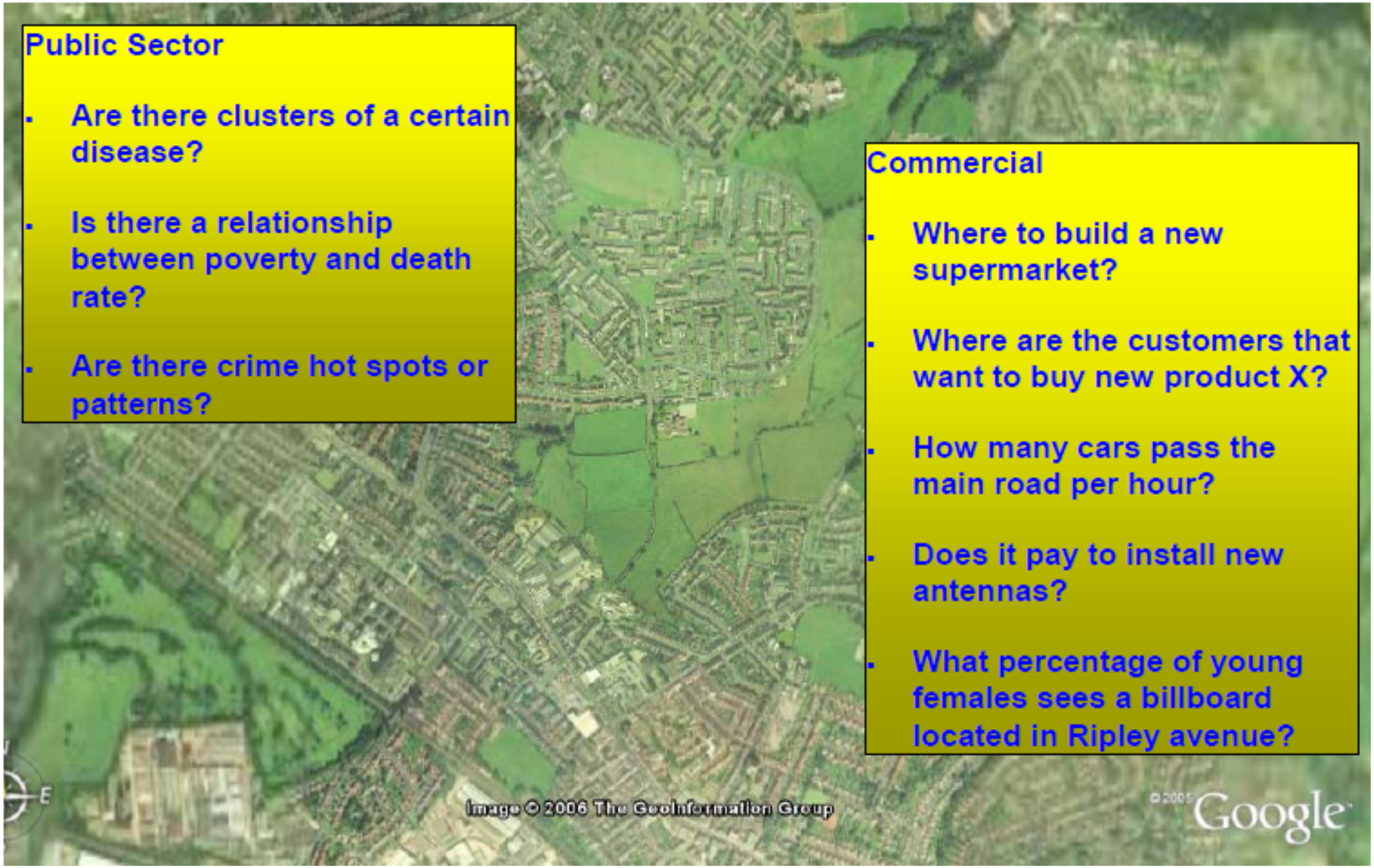
Introduction to Spatial Data Mining

Public Sector

- Are there clusters of a certain disease?
- Is there a relationship between poverty and death rate?
- Are there crime hot spots or patterns?

Commercial

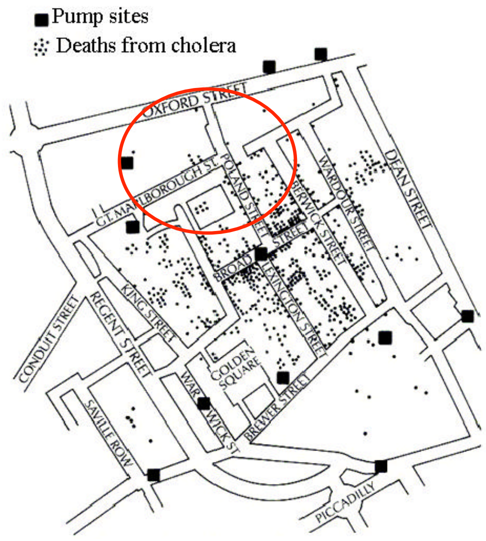
- Where to build a new supermarket?
- Where are the customers that want to buy new product X?
- How many cars pass the main road per hour?
- Does it pay to install new antennas?
- What percentage of young females sees a billboard located in Ripley avenue?



Examples of Spatial Patterns

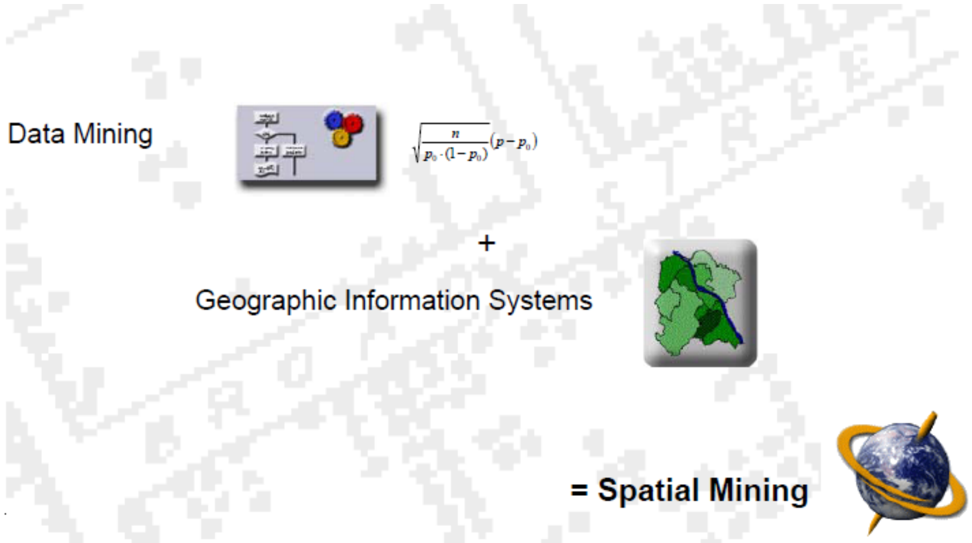
- Historical example
  - 1855 Asiatic Cholera in London: a water pump identified as the source

- Modern Examples
  - Cancer clusters to investigate environment health hazards
  - Crime hotspots for planning police patrol routes
  - Bald eagles nest on tall trees near open water
  - Nile virus spreading from north east USA to south and west
  - Unusual warming of Pacific ocean (El Nino) affects weather in USA



Spatial vs. Geographic Data Mining

- Spatial vs. Geographic Data Mining
  - Geographic Data is data related to the Earth
  - Spatial Data Mining deals with physical space in general, from molecular to astronomical level
- Geographic Data Mining is a subset of Spatial Data Mining
  - Almost all geographic data mining algorithms can work in a general spatial setting (with the same dimensionality)



What is a Spatial Pattern?

- What is not a pattern?
  - Random, haphazard, chance, stray, accidental, unexpected
  - Without definite direction, trend, rule, method, design, aim, purpose
  - Accidental - without design, outside regular course of things
  - Casual - absence of pre-arrangement, relatively unimportant
  - Fortuitous - What occurs without known cause

- What is a pattern?
  - A frequent arrangement, configuration, composition, regularity
  - A rule, law, method, design, description
  - A major direction, trend, prediction
  - A significant surface irregularity or unevenness

What is Spatial Data Mining?

- Metaphors
  - Mining nuggets of information embedded in large databases
    - Nuggets = interesting, useful, unexpected spatial patterns
    - Mining = looking for nuggets
  - Needle in a haystack

- Defining Spatial Data Mining
  - Search for spatial patterns
  - **Non-trivial search** - as "automated" as possible—reduce human effort
  - **Interesting, useful** and **unexpected** spatial pattern

What is Spatial Data Mining?

- Non-trivial search for **interesting** and **unexpected** spatial pattern
- Non-trivial Search
  - Large (e.g. exponential) search space of plausible hypothesis
  - Ex. Asiatic cholera : causes: water, food, air, insects, …; water delivery mechanisms - numerous pumps, rivers, ponds, wells, pipes, ...
- Interesting
  - Useful in certain application domain
  - Ex. Shutting off identified Water pump => saved human life
- Unexpected
  - Pattern is not common knowledge
  - May provide a new understanding of world
  - Ex. Water pump - Cholera connection lead to the "germ" theory

What is NOT Spatial Data Mining?

- Simple Querying of Spatial Data
  - Find neighbors of Canada given names and boundaries of all countries
  - Find shortest path from Boston to Houston in a freeway map
  - Search space is not large (not exponential)
- Testing a hypothesis via a primary data analysis
  - Ex. Female chimpanzee territories are smaller than male territories
  - Search space is not large !
  - SDM: secondary data analysis to generate multiple plausible hypotheses
- Uninteresting or obvious patterns in spatial data
  - Heavy rainfall in Minneapolis is correlated with heavy rainfall in St. Paul, Given that the two cities are 10 miles apart.
  - Common knowledge: Nearby places have similar rainfall
- Mining of non-spatial data
  - Diaper sales and beer sales are correlated in evenings
  - GPS product buyers are of 3 kinds:
    - outdoors enthusiasts, farmers, technology enthusiasts

Why Learn about Spatial Data Mining?

- Two basic reasons for new work
  - Consideration of use in certain application domains
  - Provide fundamental new understanding

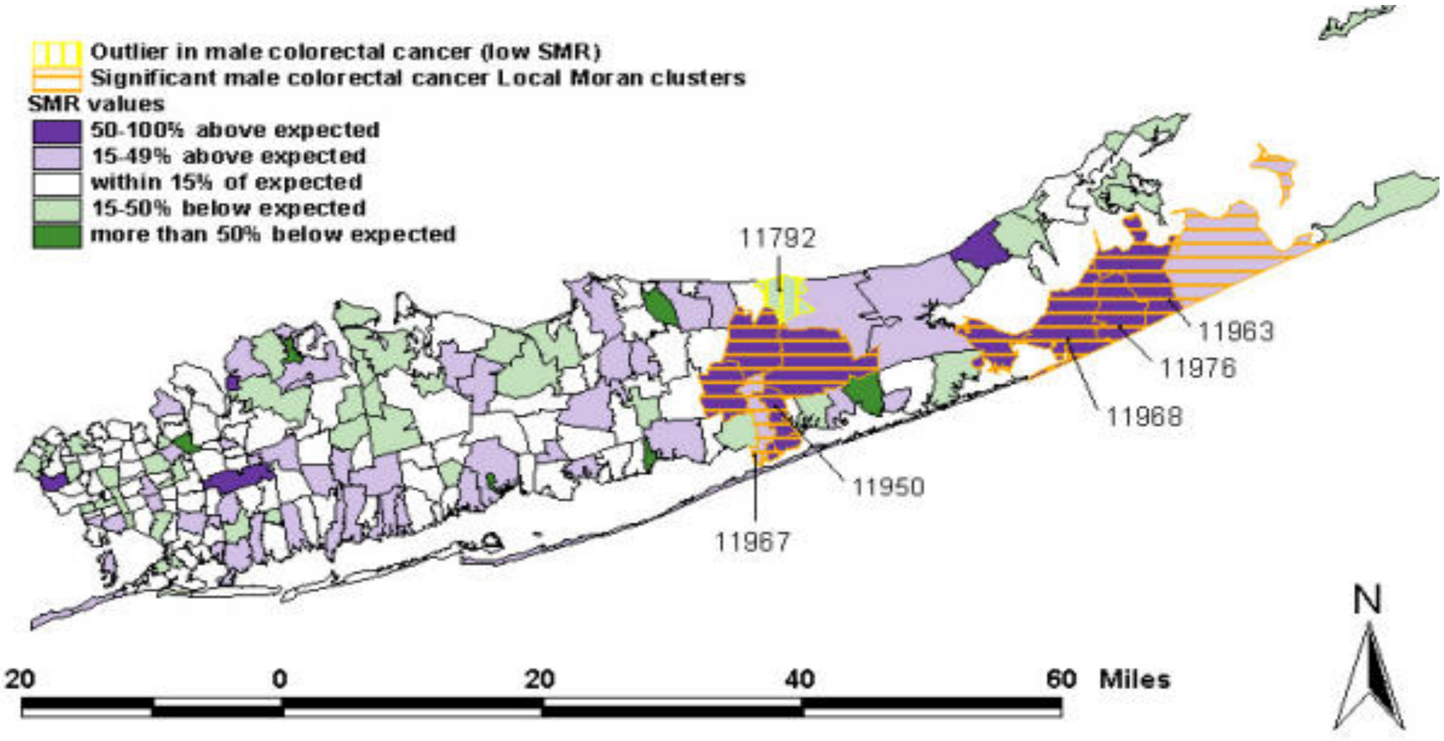
- Application domains
  - Scale up secondary spatial (statistical) analysis to very large datasets
    - Describe/explain locations of human settlements in last 5000 years
    - Find cancer clusters to locate hazardous environments
    - Prepare land-use maps from satellite imagery
    - Predict habitat suitable for endangered species
  - Find new spatial patterns
    - Find groups of co-located geographic features

Why Learn about Spatial Data Mining?

- New understanding of geographic processes for Critical questions
  - Ex. How is the health of planet Earth?
  - Ex. Characterize effects of human activity on environment and ecology
  - Ex. Predict effect of El Nino on weather, and economy
- Traditional approach: manually generate and test hypothesis
  - But, spatial data is growing too fast to analyze manually
    - Satellite imagery, GPS tracks, sensors on highways, ...
  - Number of possible geographic hypothesis too large to explore manually
    - Large number of geographic features and locations
    - Number of interacting subsets of features grow exponentially
    - Ex. Find connections between weather events across ocean and land areas
- SDM may reduce the set of plausible hypothesis
  - Identify hypothesis supported by the data
  - For further exploration using traditional statistical methods

Example

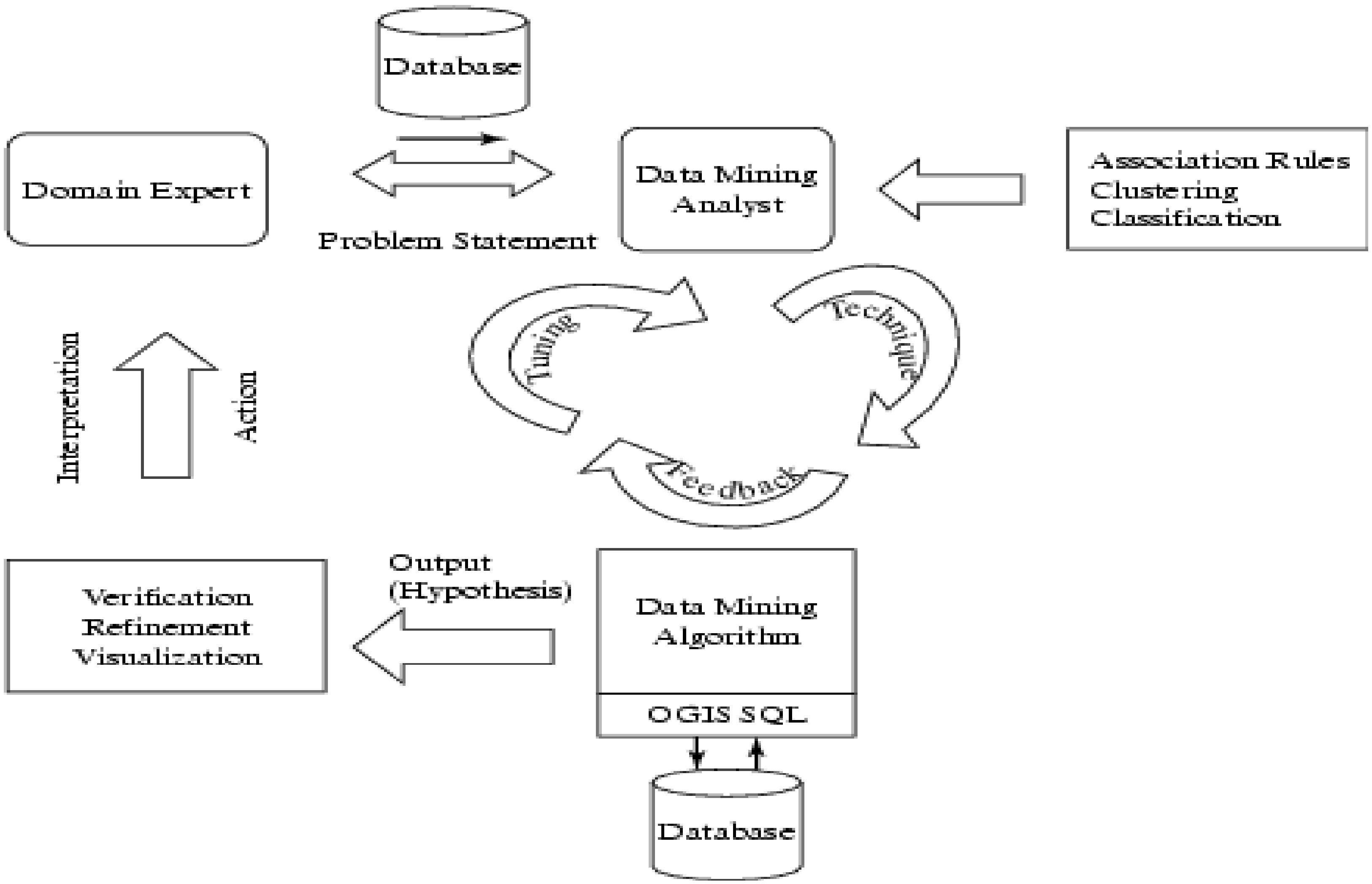
- What is the overall pattern of colorectal cancer
- Is there clustering of high colorectal cancer incidence anywhere in the study area
- Where is colorectal cancer risk significantly elevated



Spatial Data Mining: Actors

- Domain Expert
  - Identifies SDM goals, spatial dataset,
  - Describe domain knowledge, e.g. well-known patterns, e.g. correlates
  - Validation of new patterns
- Data Mining Analyst
  - Helps identify pattern families, SDM techniques to be used
  - Explain the SDM outputs to Domain Expert
- Joint effort
  - Feature selection
  - Selection of patterns for further exploration

Spatial Data Mining Process



Families of SDM Patterns

- Common families of spatial patterns
  - Classification
  - Clustering
  - Spatial Association Rules
  - Co-location
  - Outliers detection
  - Trajectories
  - …
- Note
  - Other families of spatial patterns may be defined
  - SDM is a growing field, which should accommodate new pattern families

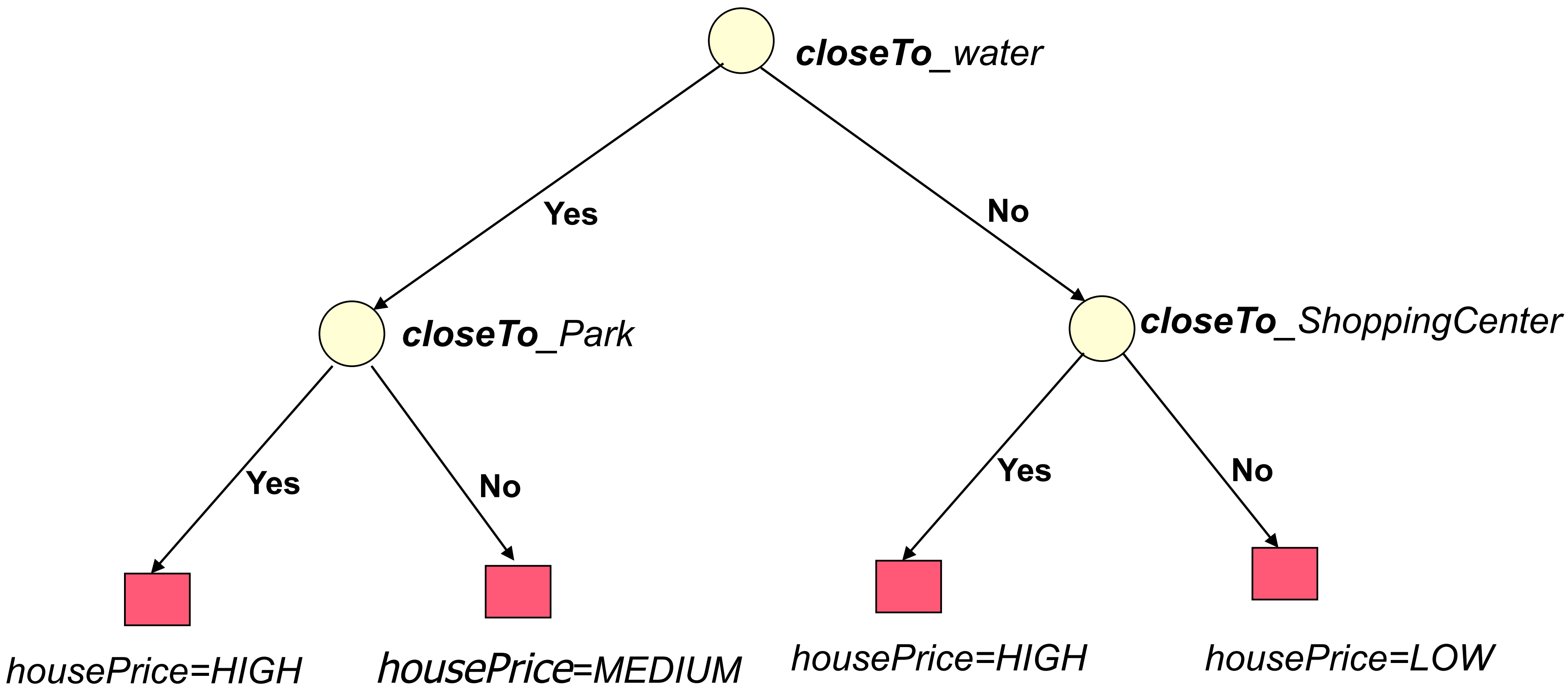
Classification

- Given a set of instances, the role of classification is to discover the classes of the instances

- Spatial objects may be characterized (classified) by different types of information (Koperski 1998):
  - non-spatial attributes (e.g. population);
  - spatially related attributes with non-spatial values (e.g. total population living within 100 meters from cellular antennas);
  - spatial predicates (e.g. closeTo_beach)

Ester (1997, 2001)

Class is a non-spatial attribute = *housePrice*
Class values: high, medium, low



Remote Sensing Data Mining

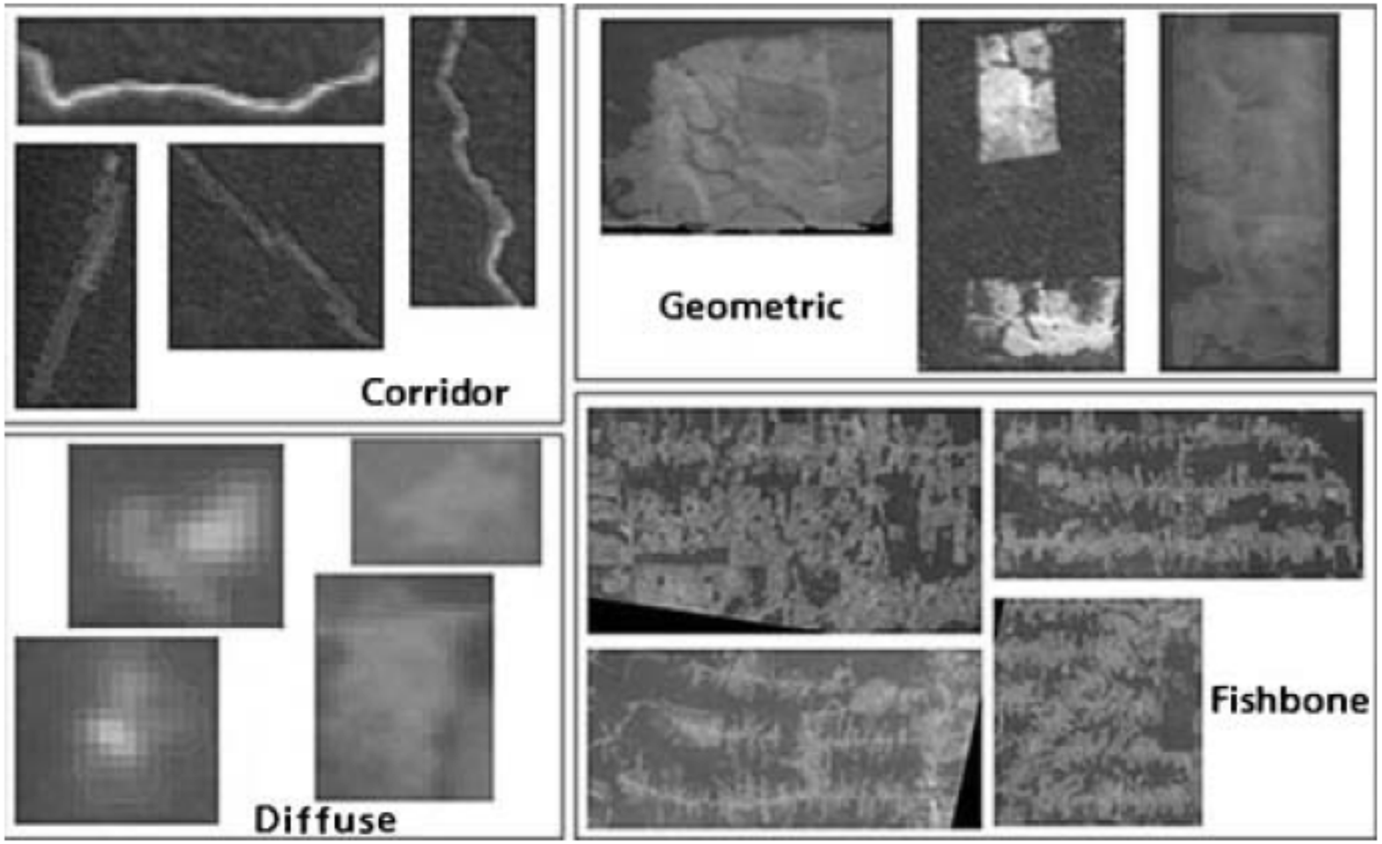


Figure 2. Examples of patterns of tropical deforestation proposed by Mertens and Lambin (1997) in the Brazilian Amazonia: corridor, diffuse, fishbone, and geometric.

Remote Sensing Data Mining

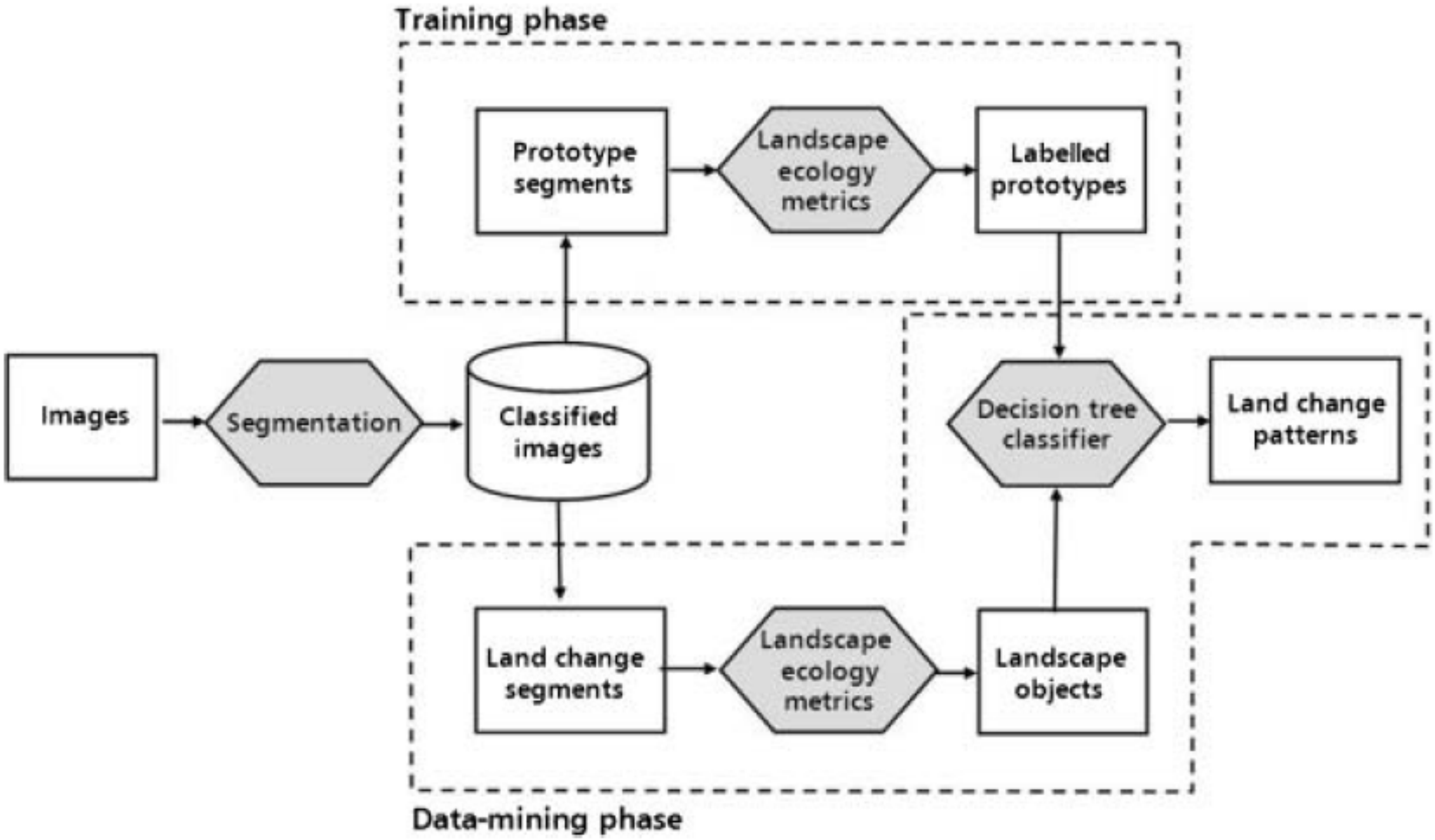


Figure 1. Proposed method for remote sensing image mining.

Metrics

- Perimeter (m):

$$\text{PERIM} = p_{ij}. \tag{1}$$

- Area (ha):

$$\text{AREA} = \left(a_{ij}/10\,000\right). \tag{2}$$

- PARA, perimeter–area ratio, a measure of shape complexity:

$$\text{PARA} = \frac{p_{ij}}{a_{ij}}. \tag{3}$$

- Shape, shape compactness index, calculated by the patch perimeter p_{ij} divided by $p_{ij\ \min}$, which is the minimum perimeter possible for a maximally compact patch of the matching patch area. It is equal to 1 when the region is a square and grows according to the region's irregularity.

$$\text{SHAPE} = \frac{p_{ij}}{p_{ij\ \min}}. \tag{4}$$

Decision Tree

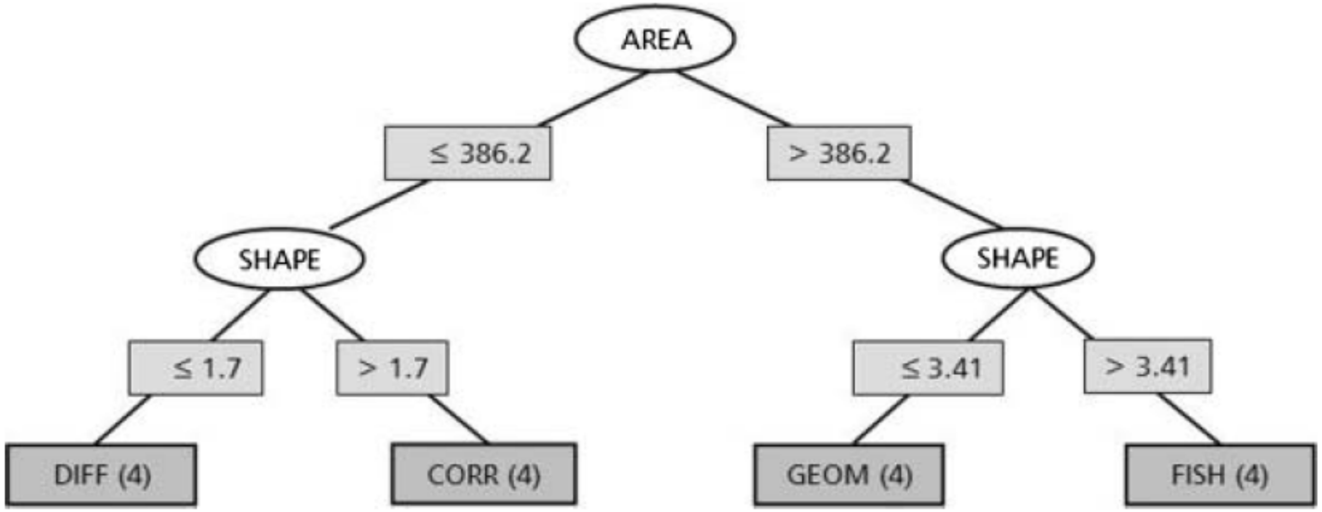


Figure 3. Decision tree for patterns in figure 3 (GEOM: geometric; FISH: fishbone; DIFF: diffuse; CORR: corridor). Metrics: area in km^2 (AREA) and shape compactness index (SHAPE).

Results

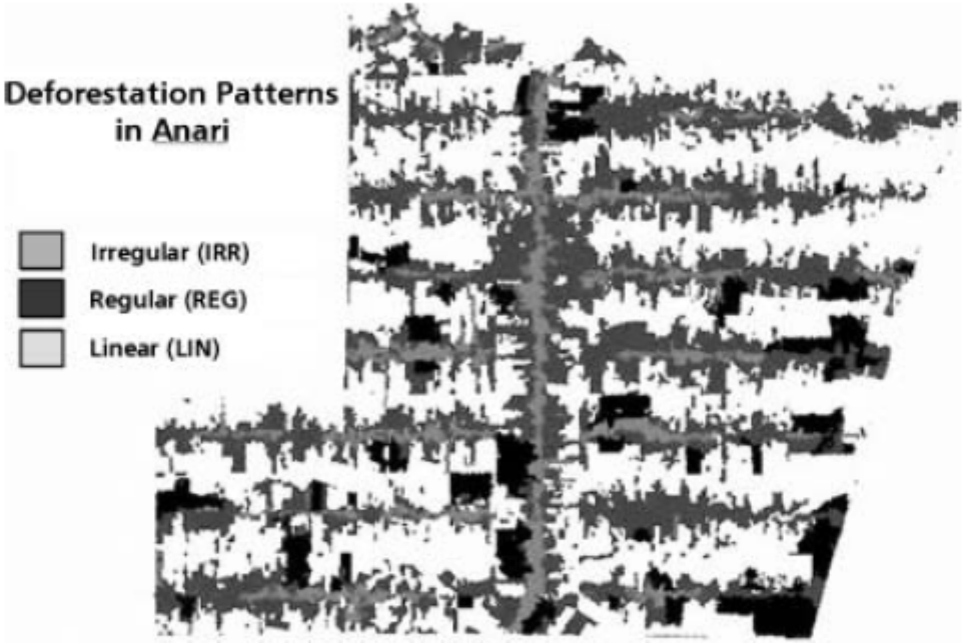


Figure 12. Cumulative deforestation patterns in Vale do Anari (1985–2000).

Mineração de dados e análise de imagens baseada em objeto aplicadas ao mapeamento de cobertura da Terra

SBSR 2013

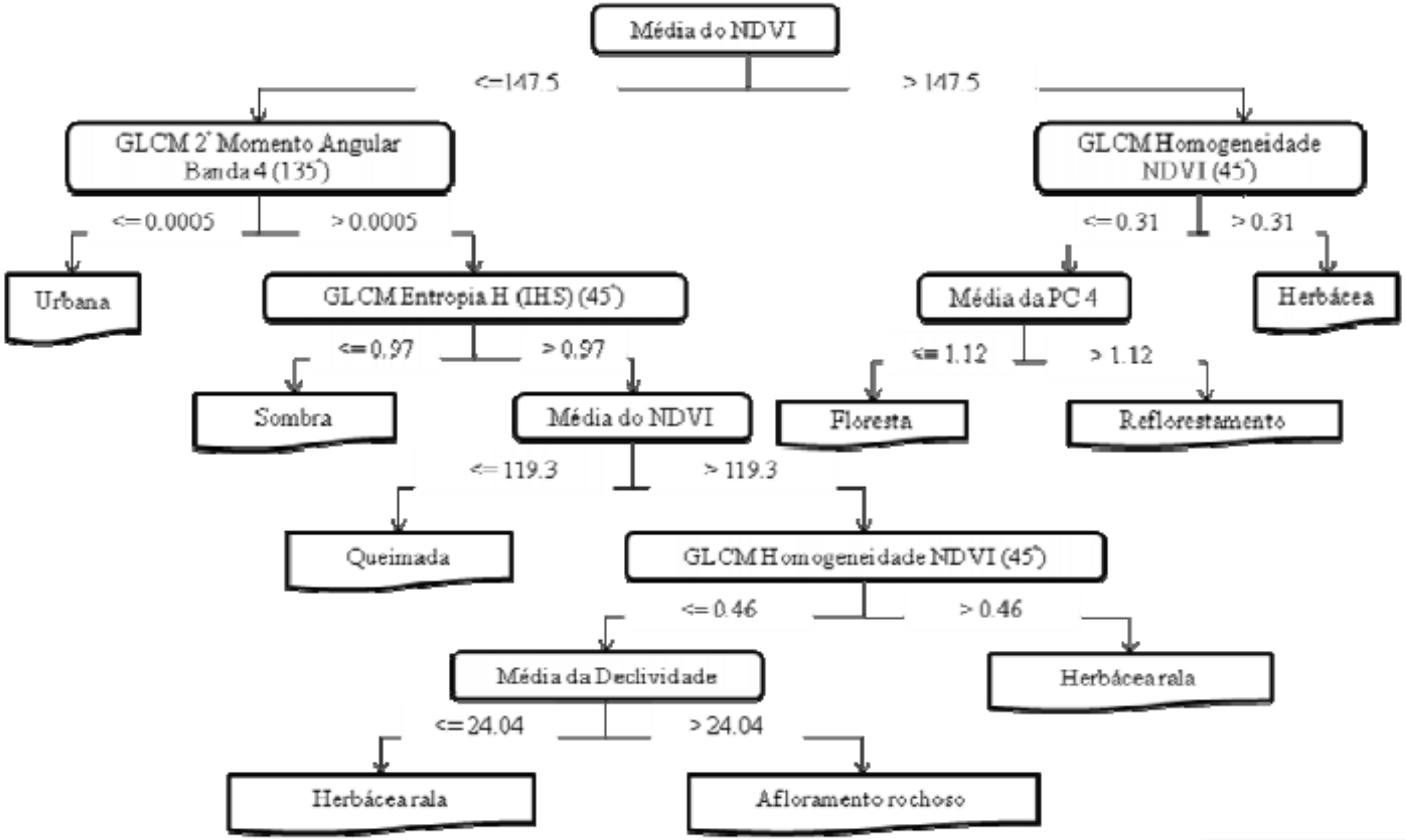


Figura 1. Árvore de decisão gerada pelo algoritmo C4

Clustering (cluster analysis)

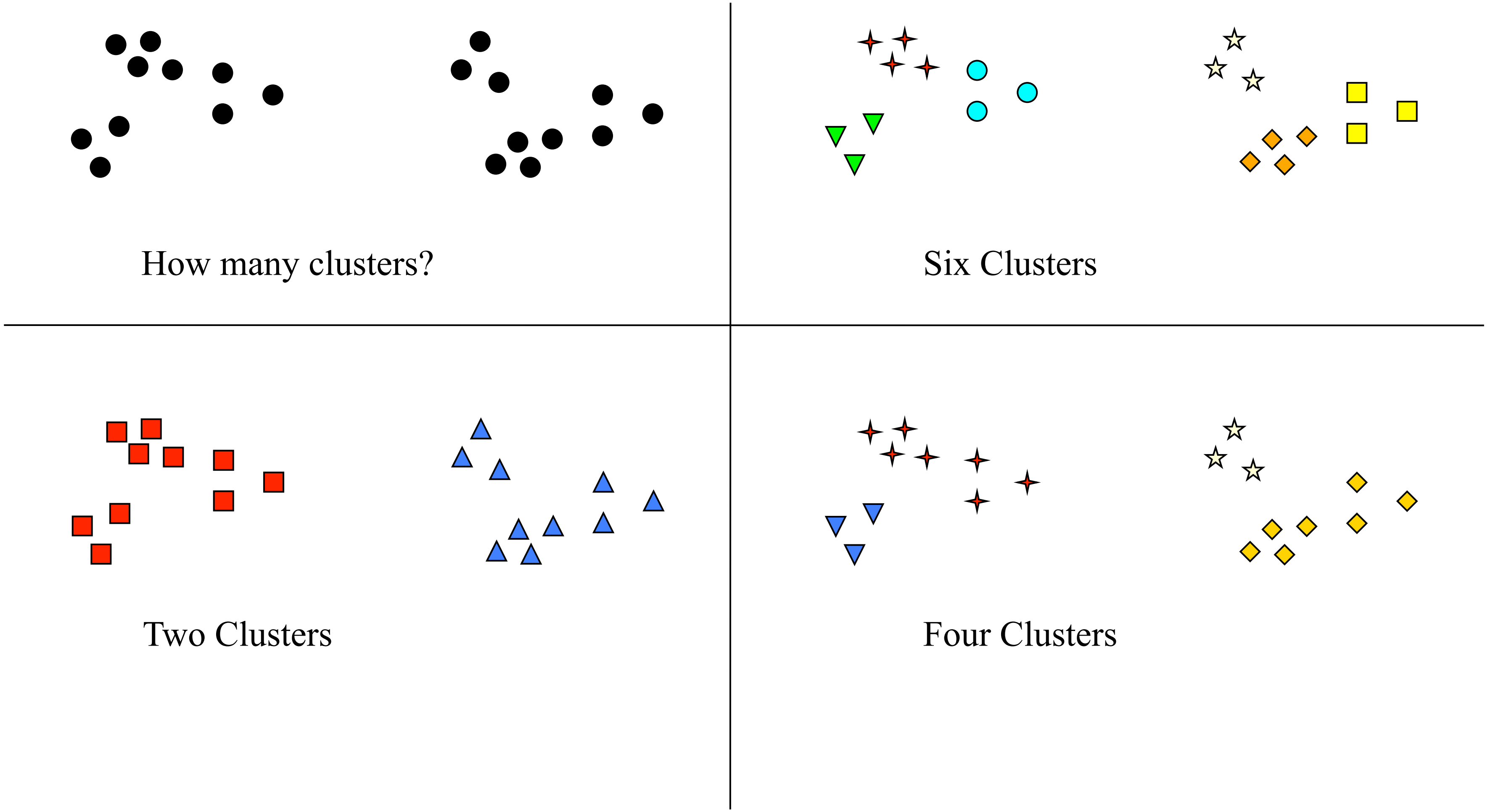
- Clustering is a process of partitioning a set of data into a set of groups called *clusters*

- A cluster is a set of data (objects) with
  - similar characteristics
  - that can be collectively treated as one group

- Clustering is an unsupervised method
  - no predefined classes

Clustering Analysis (Kumar 2005)

Different ways of clustering the same set of points



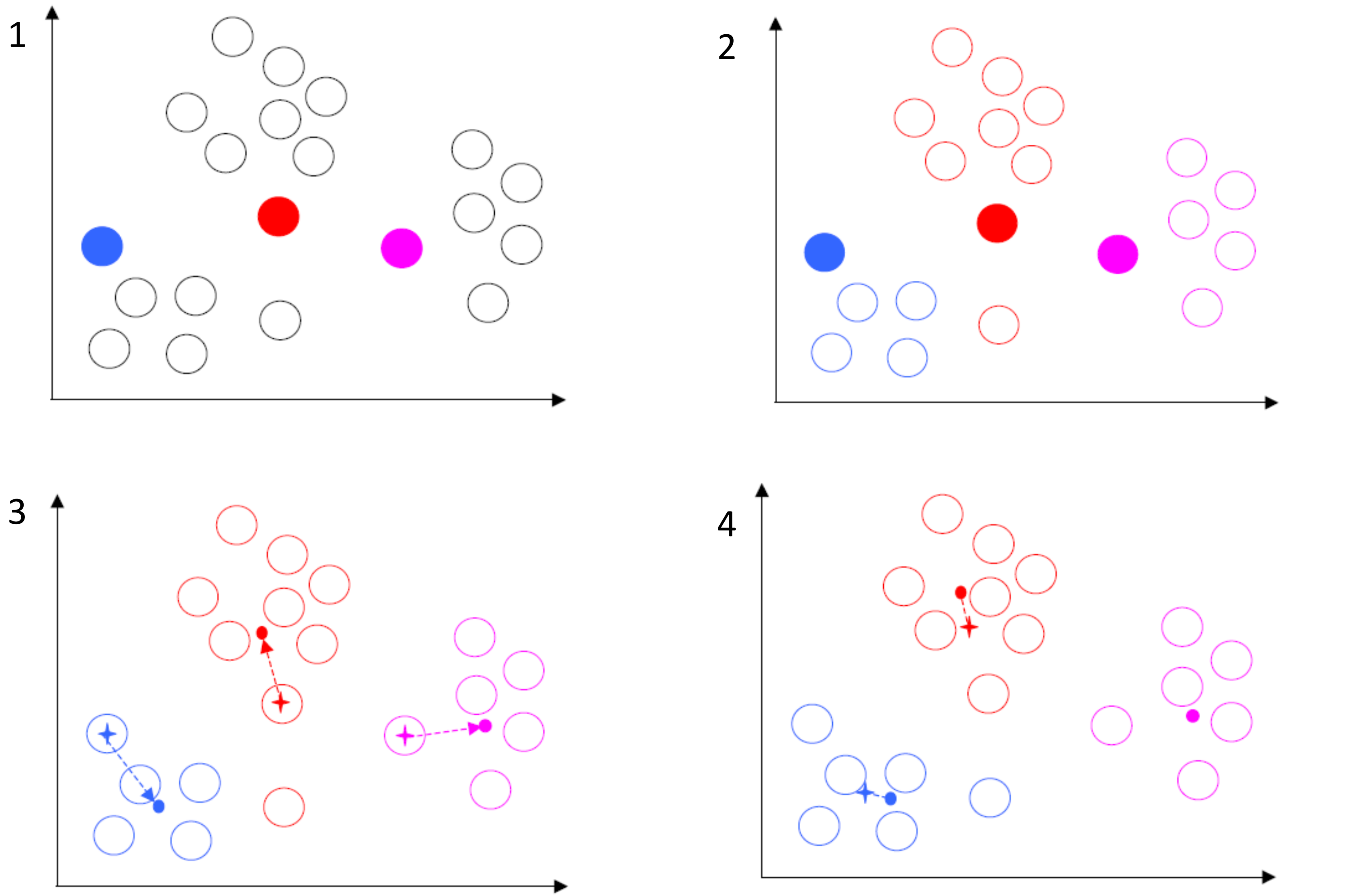
Main Clustering Approaches

- Partitioning
  - A division of data objects into non-overlapping subsets (clusters) such that each object is in exactly one subset
- Hierarchical
  - A set of nested clusters organized as a hierarchical tree
- Density-based
  - Find clusters based on density of regions
- Grid-based
  - Find clusters based on the number of points in each cell

K-means

- Partitional clustering approach
- Each cluster is associated with a centroid
- Each point is assigned to the cluster with the closest centroid
- A drawback of the k-means is that the number of clusters K is an input parameter

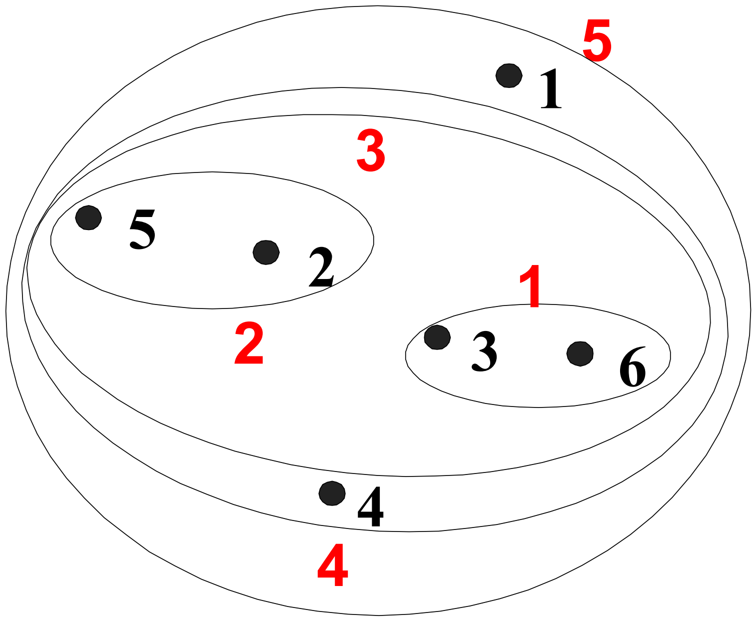
K-means

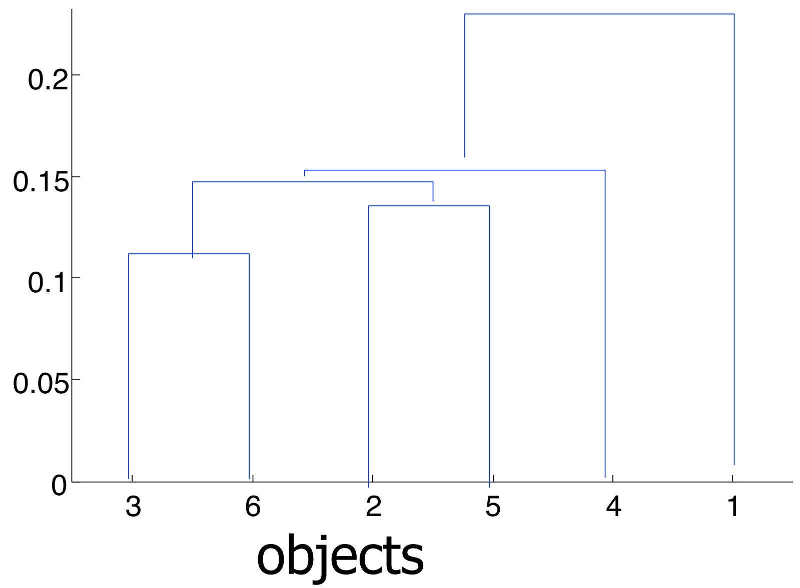


Hierarchical Clustering

Two main types: Agglomerative and Divisive

- Agglomerative
  - Start with all objects as individual clusters
  - At each step, merge the two most similar clusters
  - Until rests one cluster (or k clusters)





Hierarchical Clustering

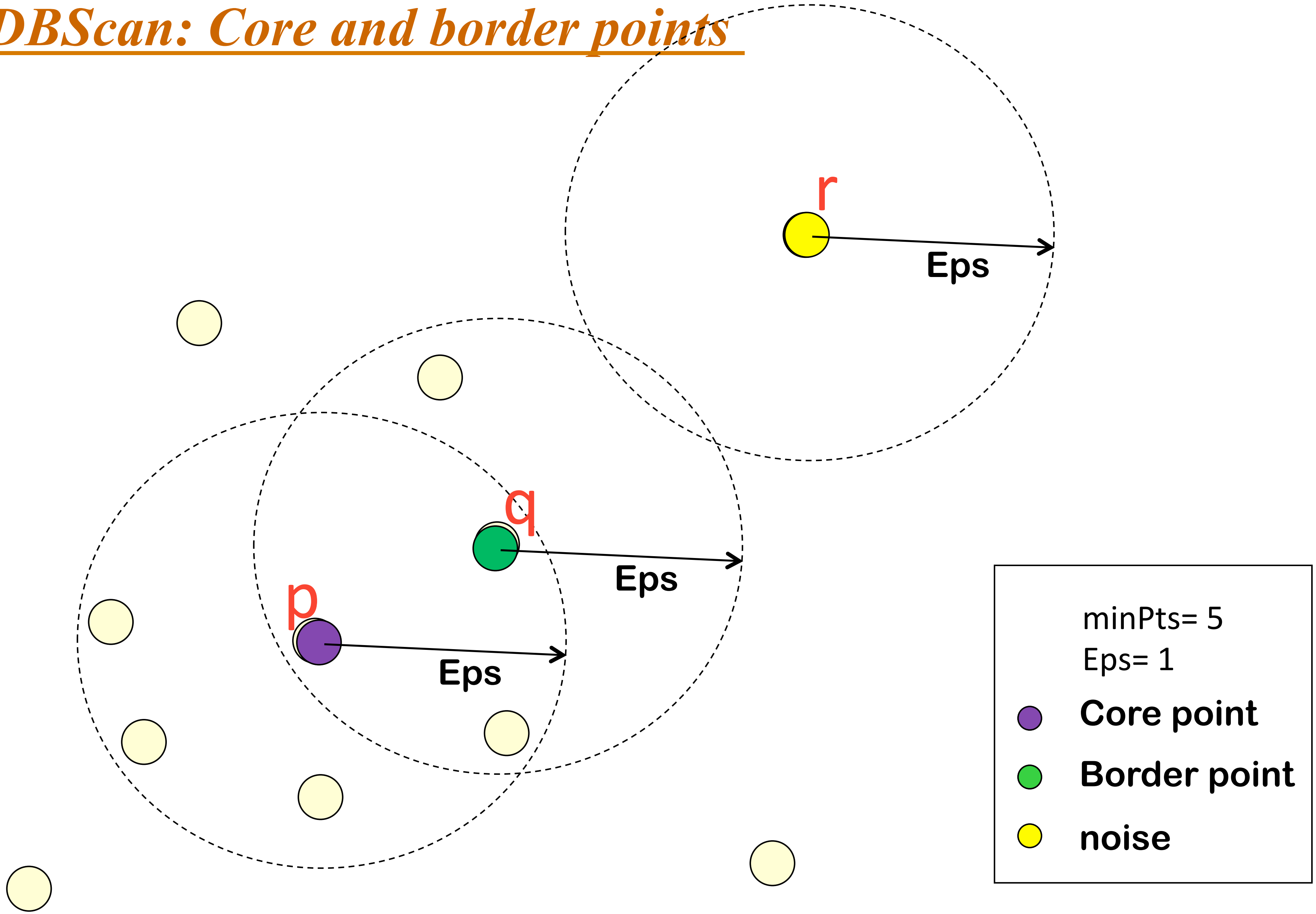
- Divisive
  - Start with one cluster (with all objects)
  - At each step, split a cluster in two
  - Until each cluster contains only one object (or k clusters)

Similarity can be euclidean distance or any other measure

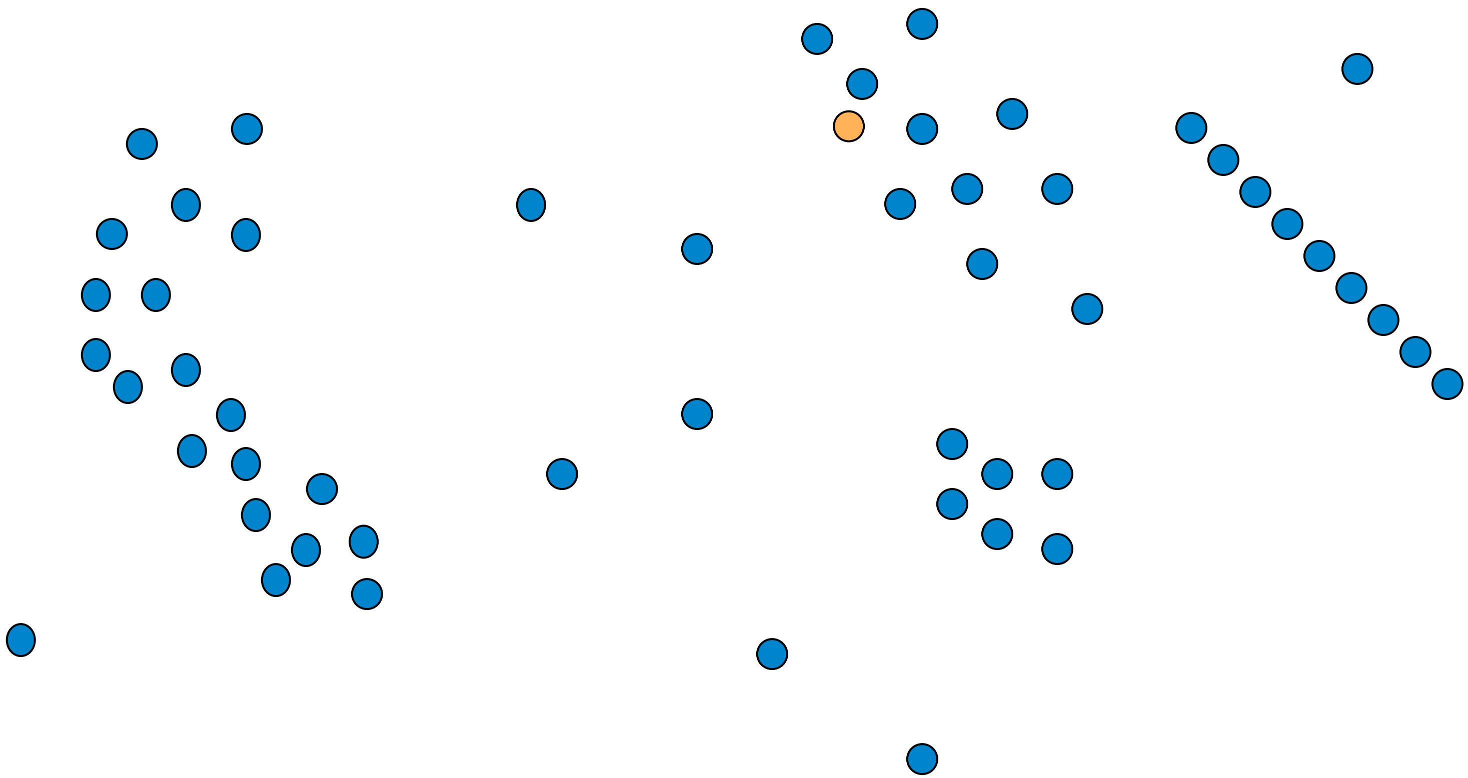
DBSCAN (Ester 1996)

- DBSCAN is a density-based algorithm
- Density = number of points within a specified radius (Eps)
- A point is a core point if it has more than a specified number of points (MinPts) within Eps
- A border point has less than MinPts within Eps, but it is in the neighborhood of a core point
- A noise point is any point that is not a core point or a border point.

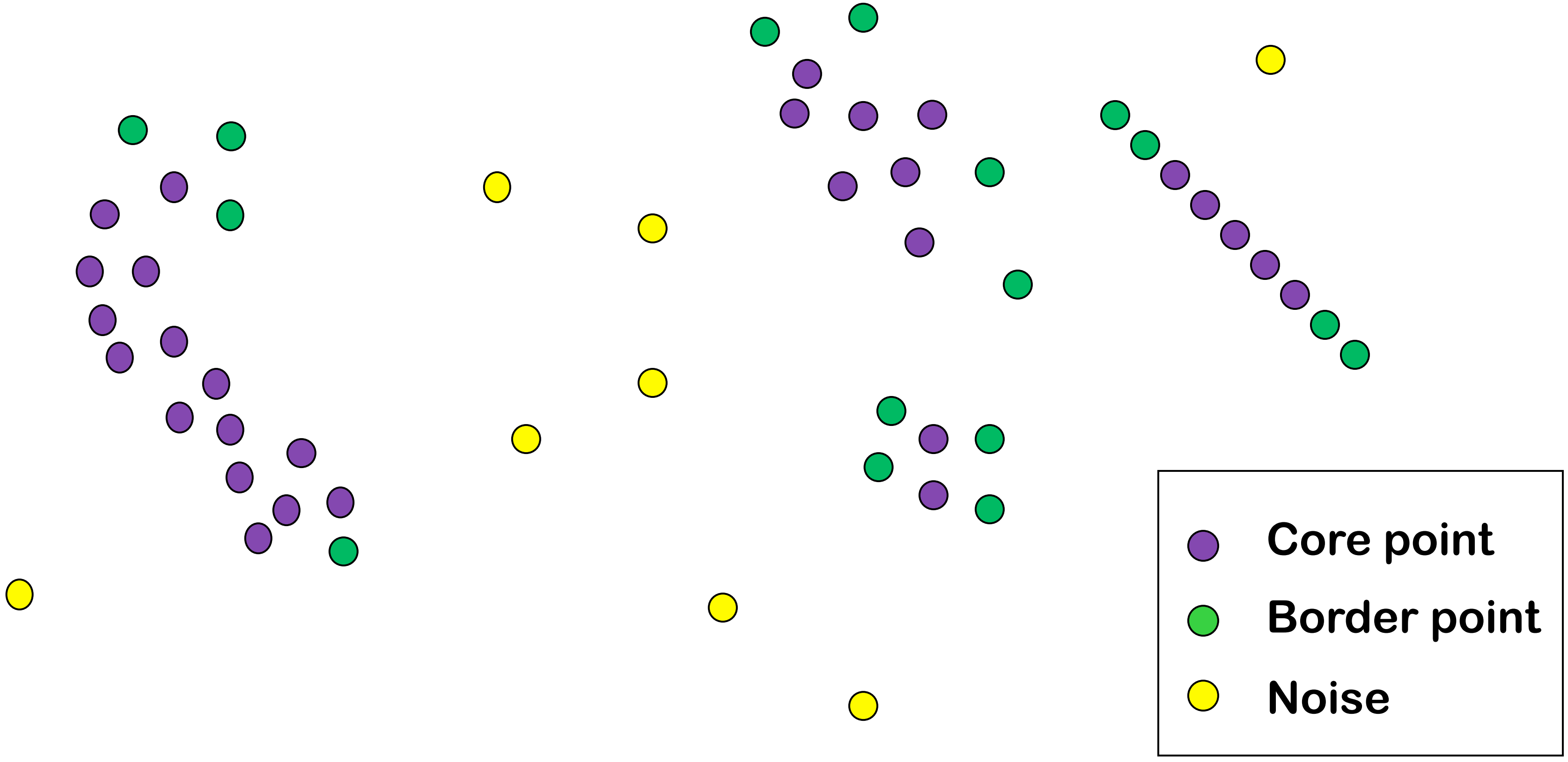
DBScan: Core and border points



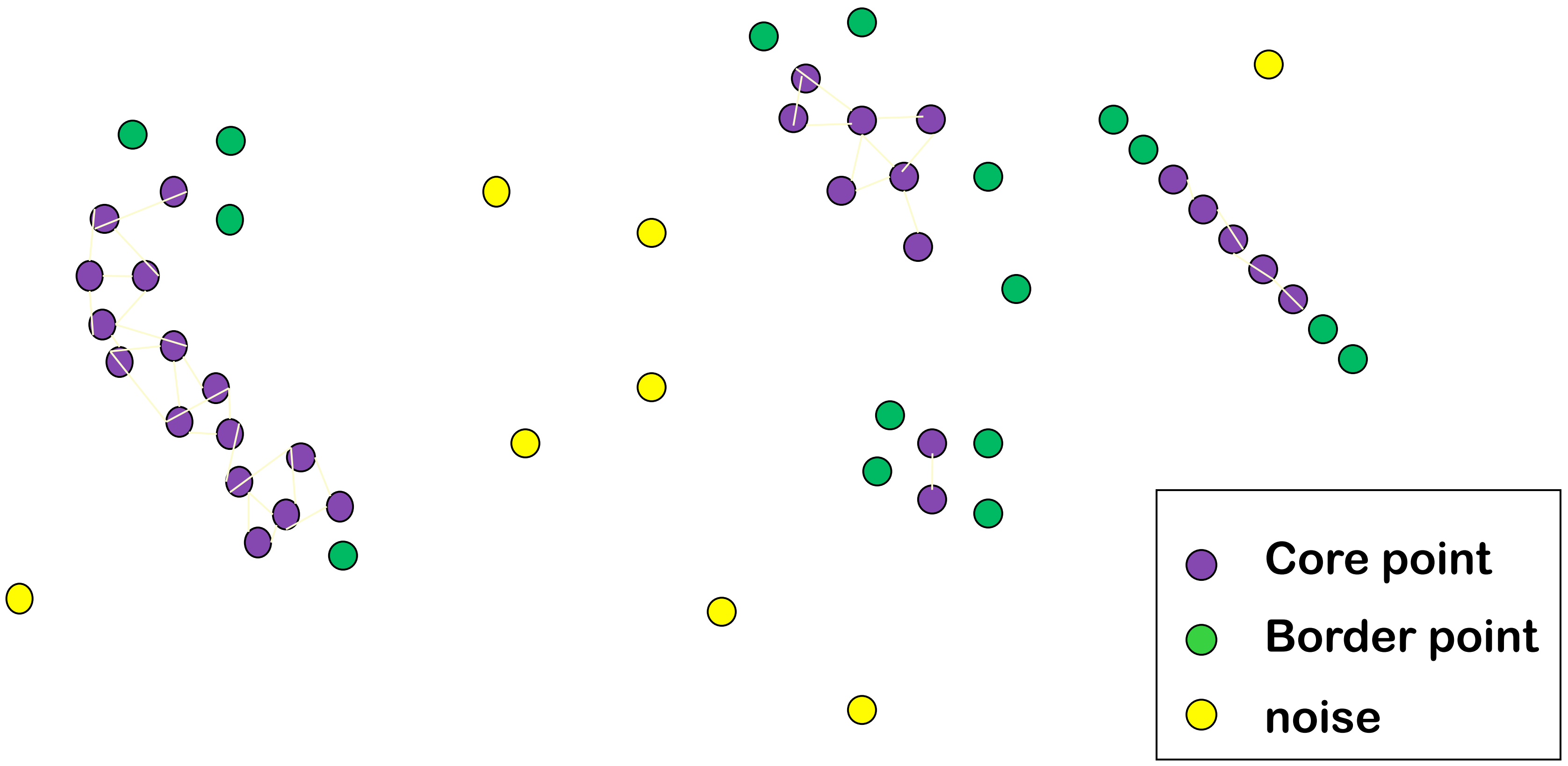
DBSCAN example



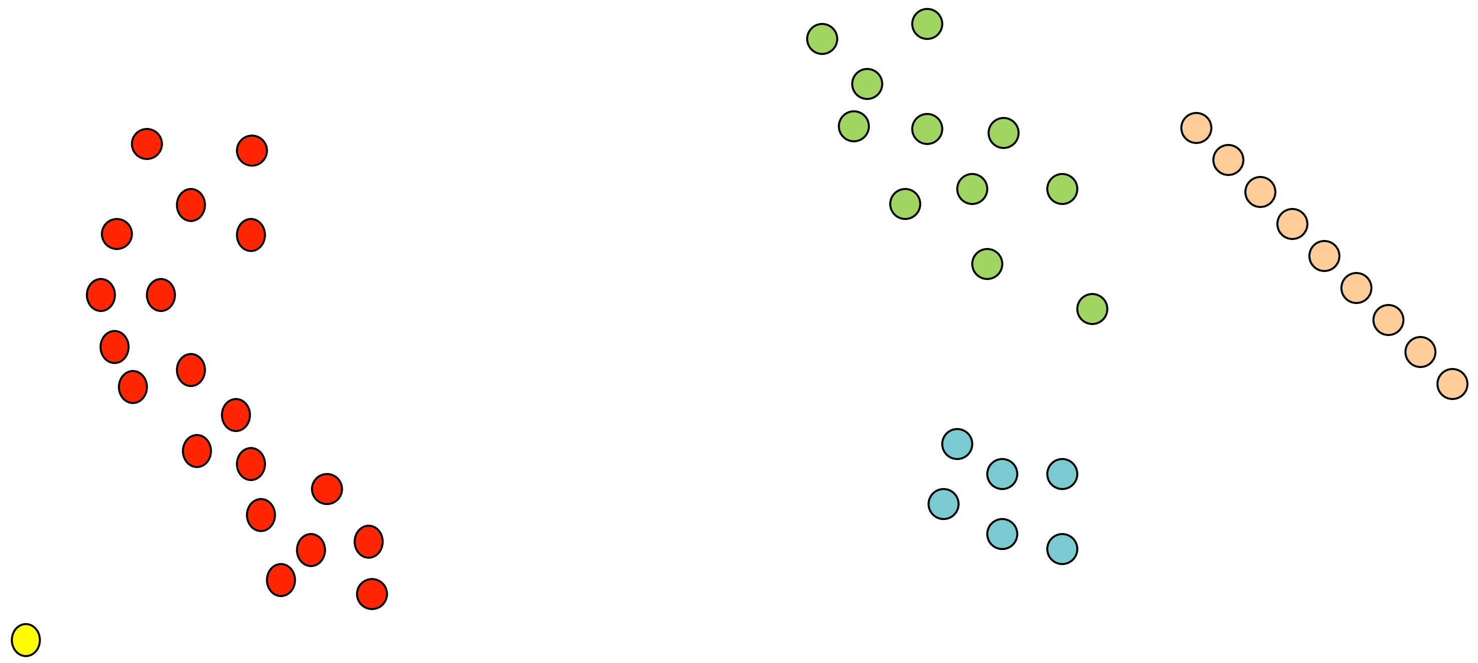
Identifying core, border and noise points



Computing distance



Final Clusters



Spatial Association Rules

Association Rules (Agrawal 1993)

- Association rule is an implication of form:

  $X \rightarrow Y$

Support: #(X∪Y) / T, where T number of transactions in the dataset

Confidence: Support(X∪Y)/Support(X)

1 **Generate frequent itemsets**

Tid	Itemset
1	A, C, D ,T, W
2	C, D, W
3	A, D, T, W
4	A, C, D, W
5	A, C, D, T, W
6	C, D, T

Set *k*	Frequent itemsets with minsup 50%
k=1	{A}, {C}, {D}, {T}, {W}
k=2	{A,C}, {A,D}, {A,T}, {A,W}, {C,D}, {C,T}, {C,W}, {D,T}, {D,W}, {T,W}
k=3	{A,C,D}, {A,C,W}, {A,D,T}, {A,D,W}, {A,T,W}, {C,D,T}, {C,D,W}, {D,T,W}
k=4	{A,C,D,W}, {A,D,T,W}

Support {AC} = 3/6 (50%)

Confidence A→C = 3/4 (75%)

2 **Extract association rules**

Associataion rules

- Main problem: generate hundreds or thousands of rules

- Frequent Itemsets: generate all possible frequent itemsets
  - Apriori-like (generate candidates) (Agrawal, 1994)
  - Pattern-growth (without candidate generation) (Han, 2000)

- Closed frequent itemsets: generate non-redundant frequent itemsets
  - Apriori-like (generate candidates) (Pasquier, 1999) (Zaki, 2000)
  - Pattern-growth (without candidate generation) (Han, 2001) (Zaki 2002)........

Redundant Rules

A Redundant rule has same support and confidence of another rule generated from the same set of transactions

Frequent Itemsets

Tid	Itemset
1	A, C, D, T, W
2	C, D, W
3	A, C, T, W
4	A, C, D, W
5	A, C, D, T, W
6	C, D, T

TidSet	Frequent itemsets with *minsup* 50%
123456	**{D}**
12456	{C}, **{C,D}**
12345	{W}, **{D,W}**
1245	{C,W}, **{C,D,W}**
1345	{A}, {A,D}, {A,W}, **{A,D,W}**
1356	{T}, **{D,T}**
145	{A,C}, {A,C,W}, {A,C,D}, **{A,C,D,W}**
135	{A,T}, {T,W}, {A,D,T}, {A,T,W}, {D,T,W}, **{A,D,T,W}**
156	{C,T}, **{C,D,T}**

A→W (suport= 4/6)
(confidence = 4/4)

A→ DW (suport = 4/6)
(confidence = 4/4)

25 frequent itemsets / 9 closed frequent itemsets

Spatial association Rules

- Spatial association rule is an implication of the form

  X → Y (support)(confidence)

- at least one element in X or Y is a spatial predicate
  - closeTo_slum → criminalityRate=High
  - Touches_beach → housePrice=High

Spatial Databases

Buildings

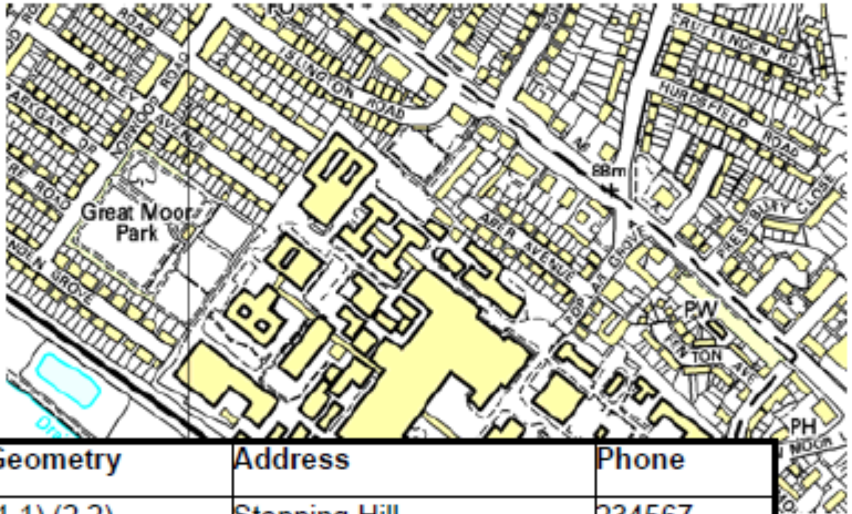
Geometry

Address

Type

...

ID	Geometry	Address	Type
1	(1,1),(2,2),...	Gladstone Street 5	1
2	(3,3),(4,4),...	Islington Road 2	2
3	(5,5),(6,6),...	Ripley Avenue 23	1



Factory

	Geometry	Name	Type
	(1,1),	Gladstone Street 5	1
2	(3,3),...	Islington Road 2	2
3	(5,5),	Ripley Avenue 23	1

Schools

	Geometry	Name	Type
	(1,1),	Gladstone Street 5	1
2	(3,3),...	Islington Road 2	2
3	(5,5),	Ripley Avenue 23	1

Streets

	Geometry	Name	Type
	(1,1),	Gladstone Street 5	1
2	(3,3),...	Islington Road 2	2
3	(5,5),	Ripley Avenue 23	1

Rivers

	Geometry	Name	Type
1	(1,1),	Gladstone Street 5	1
2	(3,3),...	Islington Road 2	2
3	(5,5),	Ripley Avenue 23	1

Hospitals

Geometry

Address

Phone

#Beds

...

ID	Geometry	Address	Phone
1	(1,1),(2,2),...	Stepping Hill	234567
2	(3,3),(4,4),...	Great Moore	567897

Description of objects are organized in relations (database tables)

Each row in a table describes one object

Different categories of objects are organized in separate relations each having its own set of attributes.

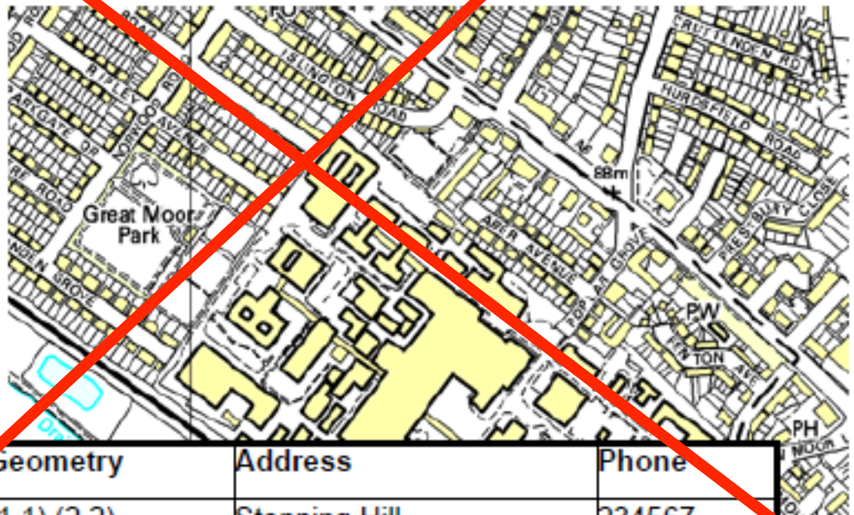
Spatial Databases

Does not fit well to standard data mining approaches!

This is where the specific research challenge for geographical data mining comes from!

Buildings
- Geometry
- Address
- Type
- ...

ID	Geometry	Address	Type
1	(1,1),(2,2),...	Gladstone Street 5	1
2	(3,3),(4,4),...	Islington Road 2	2
3	(5,5),(6,6),...	Ripley Avenue 23	1



Hospitals
- Geometry
- Address
- Phone
- #Beds
- ...

ID	Geometry	Address	Phone
1	(1,1),(2,2),...	Stepping Hill	234567
2	(3,3),(4,4),...	Great Moore	567897

Factory

ID	Geometry	Name	Type
1	(1,1),	Gladstone Street 5	1
2	(3,3),...	Islington Road 2	2
3	(5,5),	Ripley Avenue 23	1

Schools

ID	Geometry	Name	Type
1	(1,1),	Gladstone Street 5	1
2	(3,3),...	Islington Road 2	2
3	(5,5),	Ripley Avenue 23	1

Streets

ID	Geometry	Name	Type
1	(1,1),	Gladstone Street 5	1
2	(3,3),...	Islington Road 2	2
3	(5,5),	Ripley Avenue 23	1

Rivers

ID	Geometry	Name	Type
1	(1,1),	Gladstone Street 5	1
2	(3,3),...	Islington Road 2	2
3	(5,5),	Ripley Avenue 23	1

Description of objects are organized in relations (database tables)

Each row in a table describes one object

Different categories of objects are organized in separate relations each having its own set of attributes.

Different Spatial Objects are Stored in Different Tables

Street

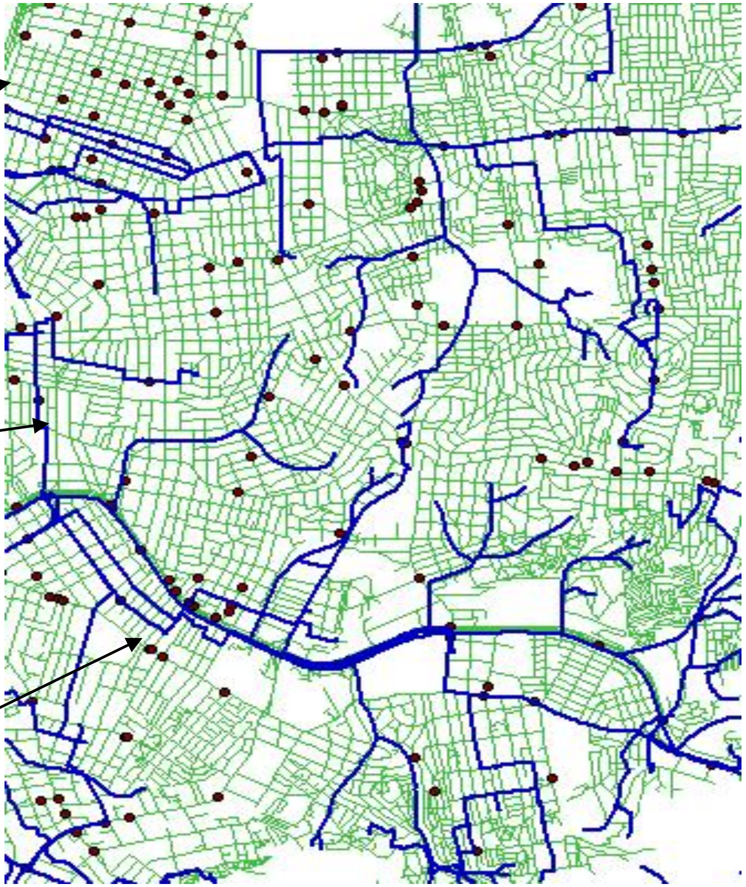
Gid	Name	Shape
1	Ijui	Multiline [(x1,y1),(x2,y2),..]
2	Lavras	Multiline [(x1,y1),(x2,y2),..]

WaterResource

Gid	Name	Shape
1	Jacui	Multiline [(x1,y1),(x2,y2),..]
2	Guaiba	Multiline [(x1,y1),(x2,y2),..]
3	Uruguai	Multiline [(x1,y1),(x2,y2),..]

GasStation

Gid	Name	VolDiesel	VolGas	Shape
1	BR	20000	85000	Point[(x1,y1)]
2	IPF	30000	95000	Point[(x1,y1)]
3	Esso	25000	120000	Point[(x1,y1)]



Most Spatial Association Rule Mining algorithms have a single table/file INPUT format

Spatial Association Rules

- Are computed in 3 main steps:
  - Data preprocessing: compute spatial relationships (spatial joins). Most expensive step
  - Compute frequent itemsets
  - Generate association rules

Different Relations (tables) need to be Spatially Joined

Preprocessed Geographic Data for Transaction-Based Data Mining

Target feature

Tuple (city)	Spatial Predicates				
1	contains(Port),	contains(Hospital)	contains(Street),	contains(Factory)	crosses(Water Body)
2		contains(Hospital),	contains(Street),		crosses(Water Body)
3	contains(Port),		contains(Street),	contains(Factory),	crosses(Water Body)
4	contains(Port),	contains(Hospital)	contains(Street),		crosses(Water Body)
5	contains(Port),	contains(Hospital)	contains(Street),	contains(Factory)	crosses(Water Body)
6		contains(Hospital),	contains(Street),	contains(Factory)	

Relevant features

Transaction Dataset X Preprocessed Spatial Dataset

Transactional Dataset

Transaction	Items
1	milk, bread, butter, cereal
2	milk, bread
3	beer, bread, chocolate
4	cereal, meet, milk
5	milk, beer, nuts, orange, cereal

- rows are transactions
- attributes are items, supposed to be independent

Spatial Dataset

Tuple (city)	Spatial Predicates
1	contains(Port), contains(Hospital), contains(TreatedWaterNet), contains(Factory), crosses(WaterBody
2	contains(Hospital), contains(TreatedWaterNet), crosses(WaterBody)
3	contains(Port), contains(TreatedWaterNet), contains(Factory), crosses(WaterBody)
4	contains(Port), contains(Hospital), contains(TreatedWaterNet), crosses(
5	contains(Port), contains(Hospital), contains(TreatedWaterNet), contains(Factory), crosses(
6	contains(Hospital), contains(TreatedWaterNet), contains(Factory)

- rows are instances of the target feature type

- attributes are predicates
- spatial predicates are spatial relationships between the target feature type and relevant feature types

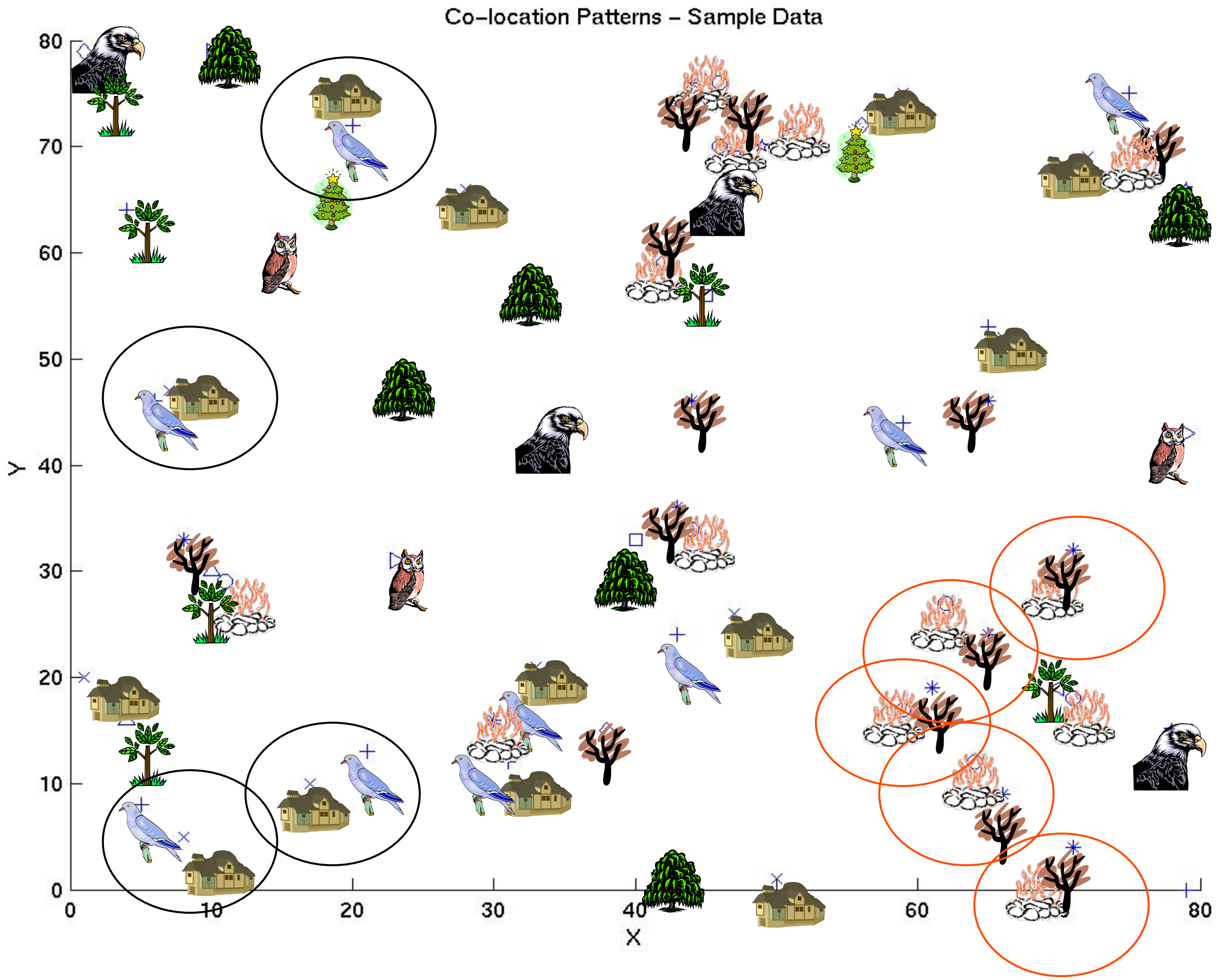
Some Spatial Association Rule Mining Algorithms

- Koperski 1995
- Spada (Appice 2003)
- Clementini (2003)
- Apriori-KC (Bogorny 2006)
- Max-FGP (Bogorny 2006ª)
- ...

- Preprocess geographic data and apply classical DM algorithms

Co-location (Shekhar 2003)

Q: find patterns from the following sample dataset

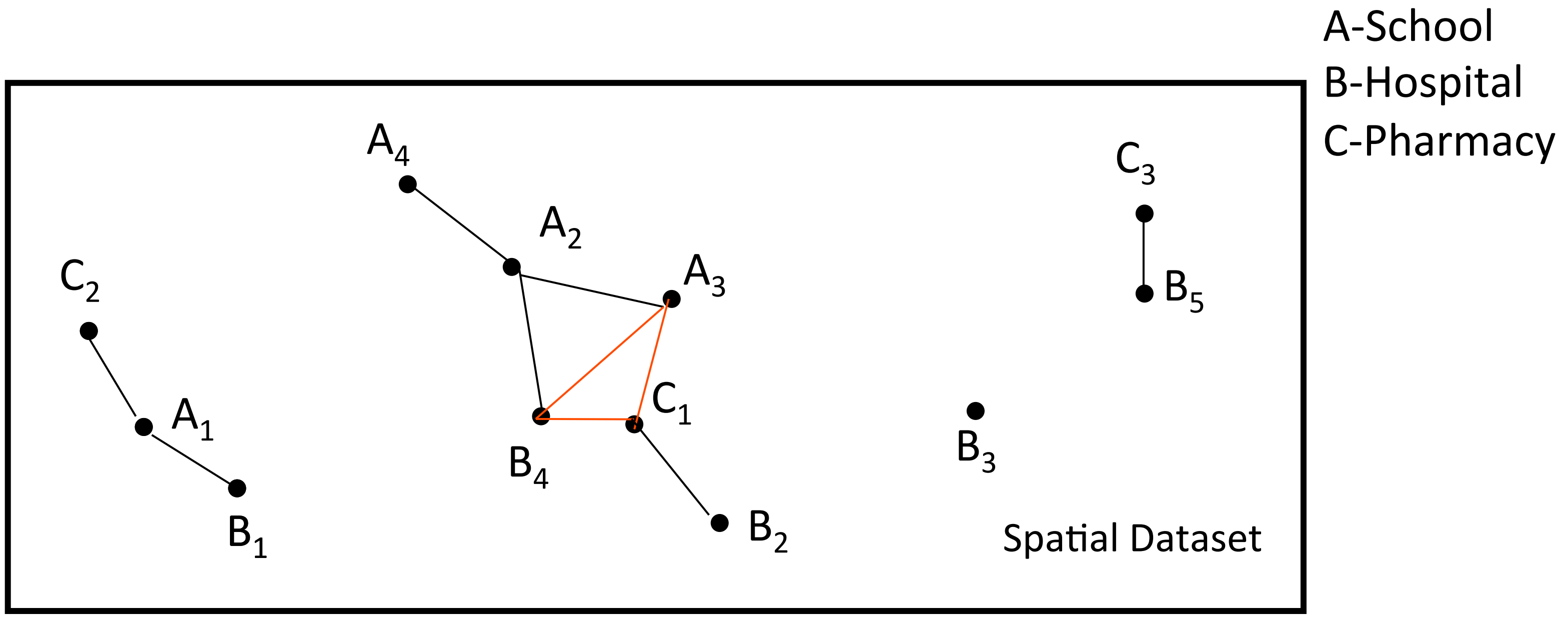


Answers:

Co-Location Patterns (Huang 2004, Yoo 2005)

- A spatial co-location pattern is a set of spatial fetatures that are frequently located together in a spatial proximity
- Input:
  - Spatial dataset
  - Distance threshold
  - Minimum participation index
- Method
  - Find neighbors
  - Find co-location candidates
  - Find frequent co-location sets
  - Extract co-location rules

Co-location Mining

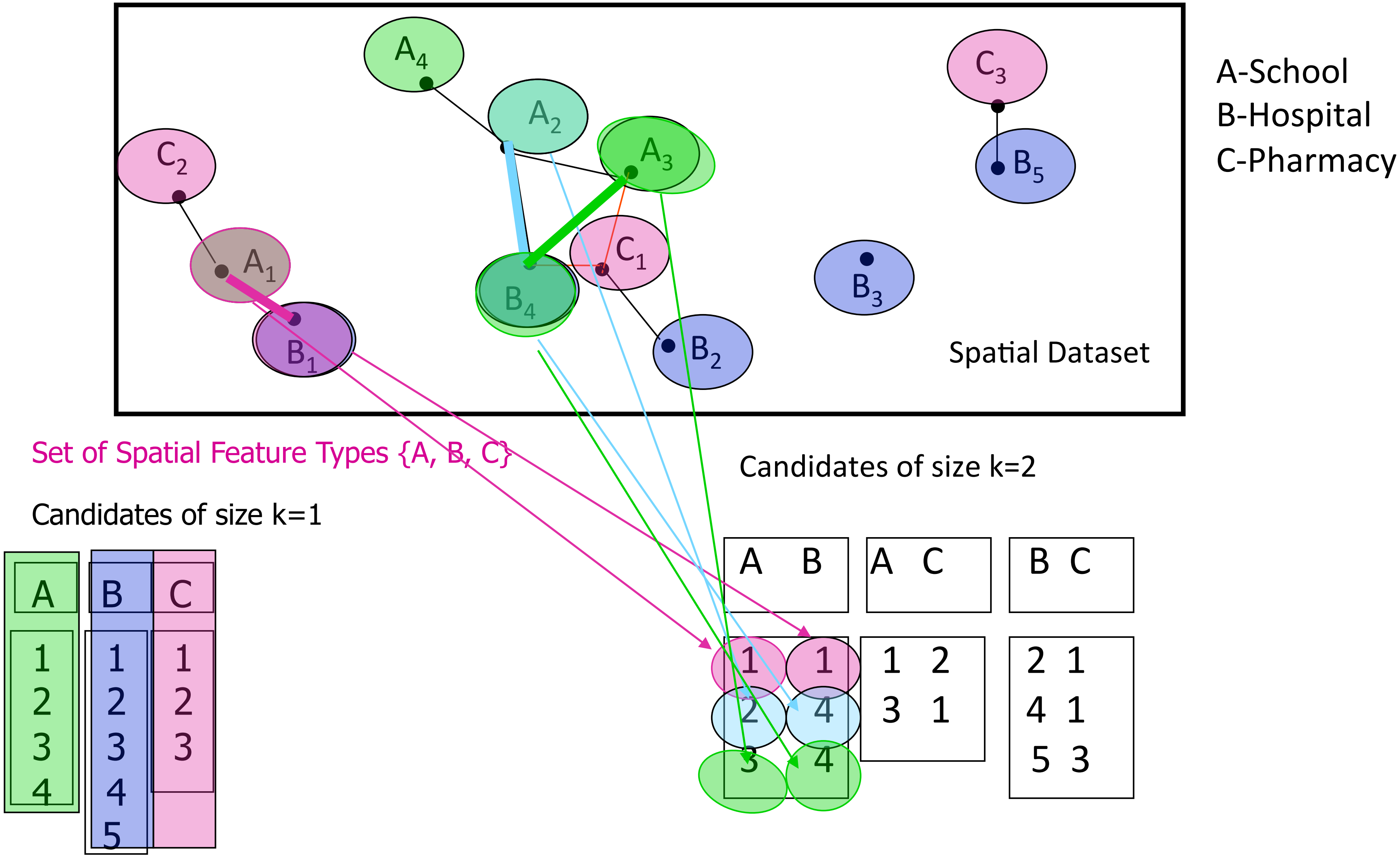


A, B, C: Spatial Feature Types

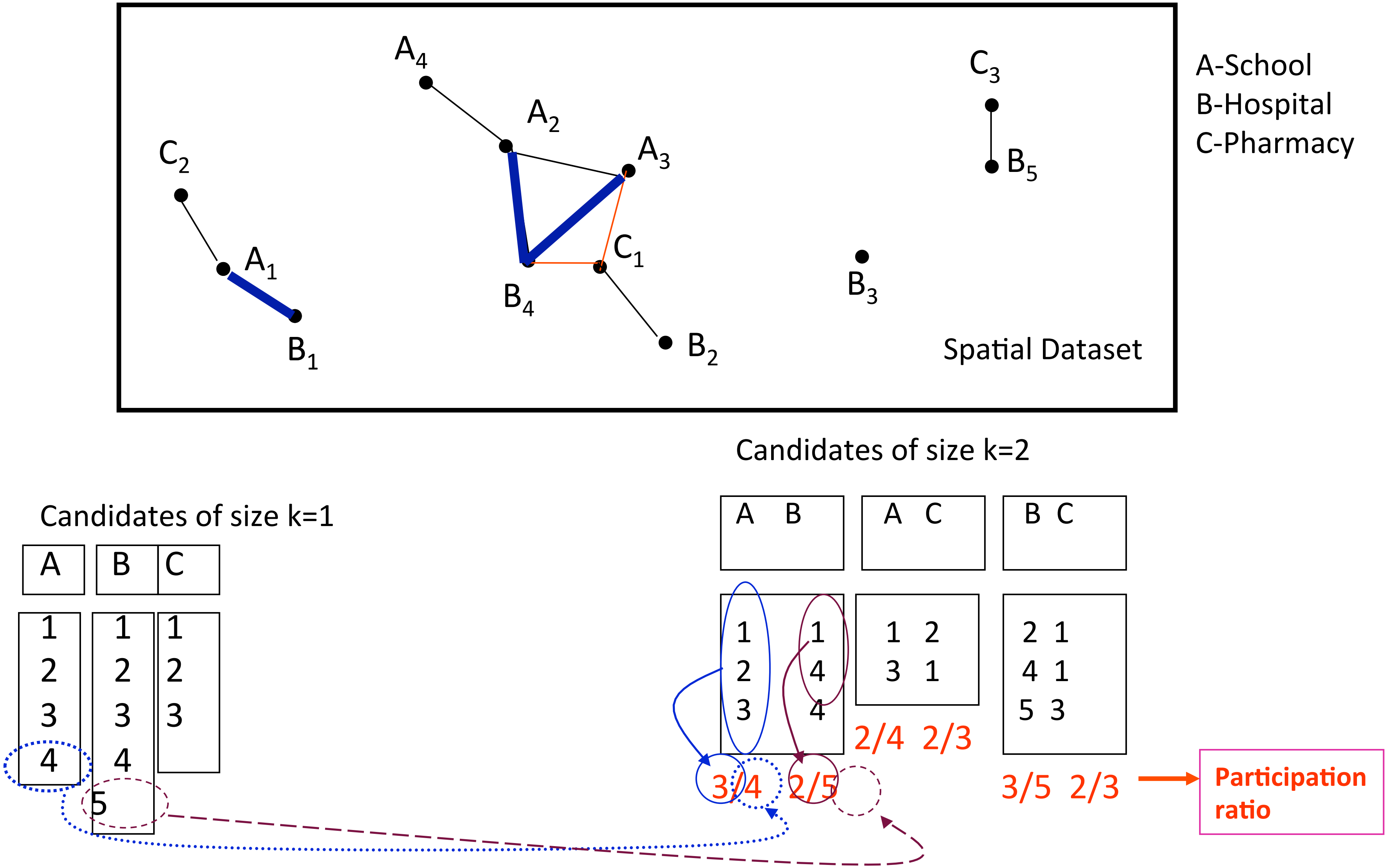
A_1, A_2... Spatial Feature Instances

Edges: neighbor

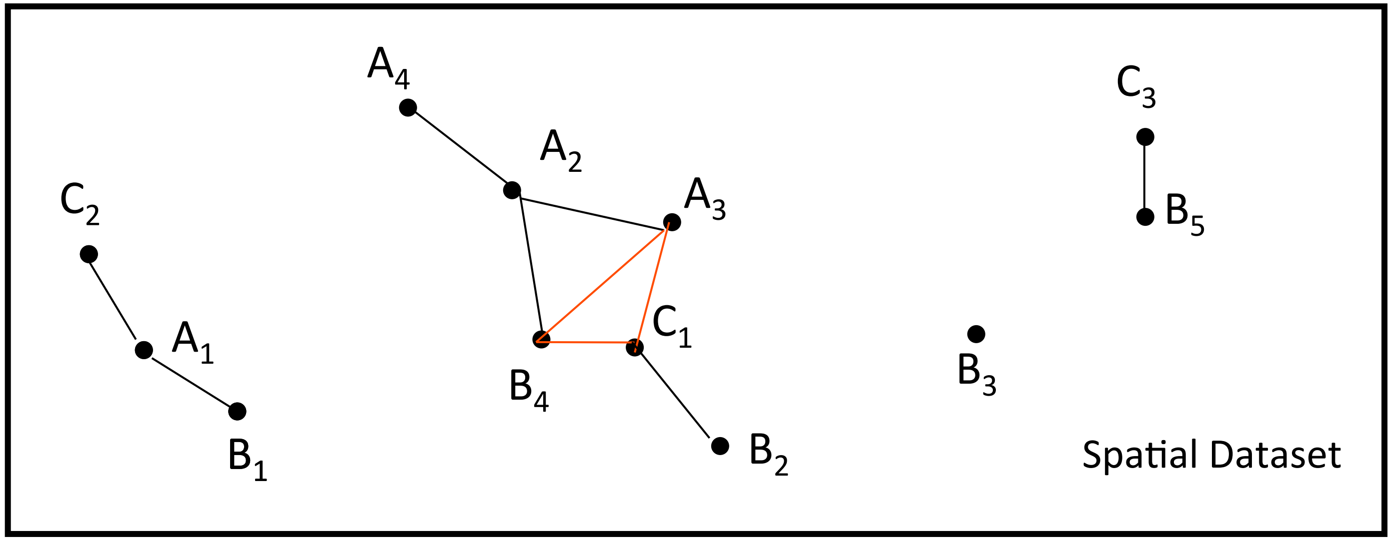
Co-location Mining



Co-location Mining



Co-location Mining



A-School
B-Hospital
C-Pharmacy

Candidates of size k=2

A	B
1	1
2	4
3	4

2/5

A	C
1	2
3	3

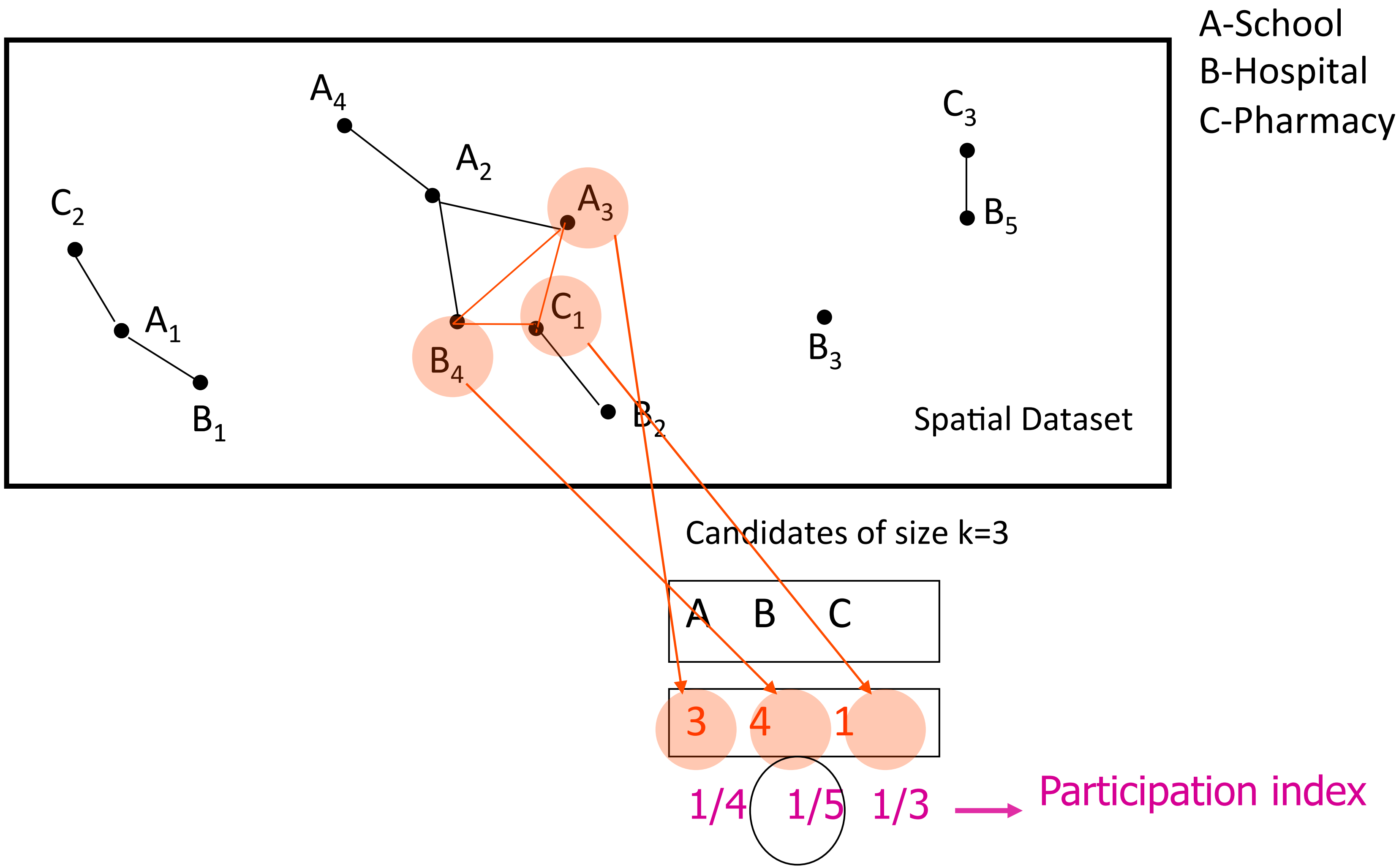
2/4

B	C
2	1
4	1
5	3

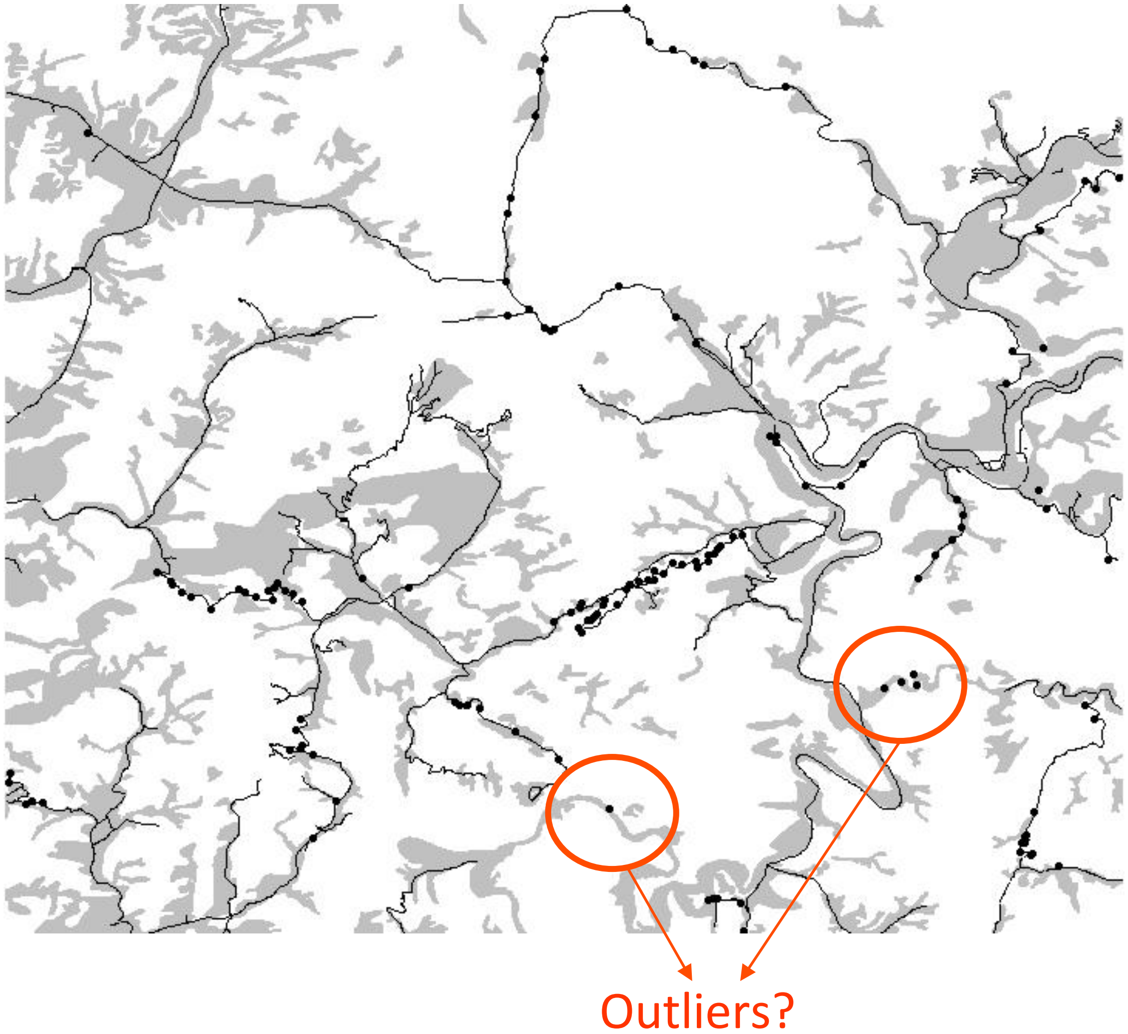
3/5

Participation Index (Lowest index)
(If participIndex>minPartIndex) → frequent set

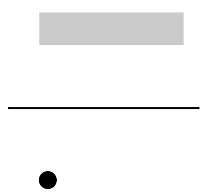
Co-location Mining



Co-location Example (Shekhar 2003)



Cropland with Roads
Roads with Bridges



Outliers

- What is an outlier?
  - Observations inconsistent with the rest of the dataset
- What is a spatial outlier?
  - Observations inconsistent with their neighborhoods
  - A local instability or discontinuity

Outliers *(Shekhar 2001, 2003)*

- **Global outliers** are data inconsistent with the rest of the data in the database
  - Applications:
    - *credit card fraud,*
    - *athlete performance analysis,*
    - *voting irregularity,*
    - *severe weather prediction*

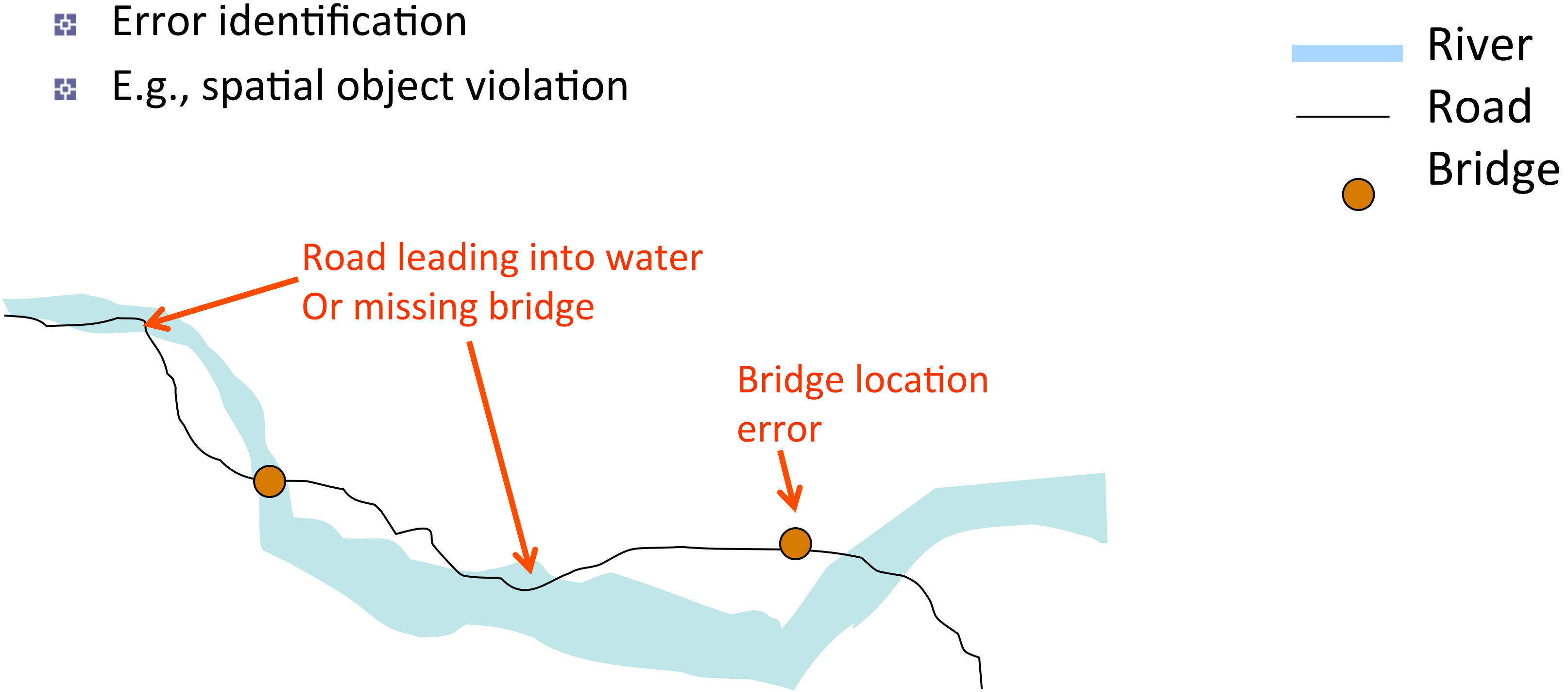
Outliers (Shekhar 2001, 2003)

- A **spatial outlier** is a spatially referenced object whose non-spatial attribute values are significantly different from those of other spatially referenced objects in its spatial neighborhood.
  - For example, a new house in an old neighborhood is a spatial outlier based on the non-spatial attribute house age

  - **Spatial attributes** are used to characterize location, neighborhood, and distance.
  - **Non-spatial attributes** are used to compare a spatial referenced object to its neighbors.

Outliers – Examples (Shekhar 2003)

- Map Production
  - Error identification
  - E.g., spatial object violation



Tools

- GeoMiner (Han 1997)
- INGENS (Malerba 2001)
- Ares (Appice 2005)
- Weka-GDPM (Bogorny 2006d)

Conclusions

- Patterns are opposite of random
- Common spatial patterns: location prediction, feature interaction, hot spots,
- SDM = search for unexpected interesting patterns in large spatial databases
- Spatial patterns may be discovered using
  - Techniques like classification, associations, clustering and outlier detection
  - New techniques are needed for SDM due to
    - Spatial Auto-correlation
    - Continuity of space

Ferramentas

- GeoMiner (Han 1997)
- INGENS (Malerba 2001)
- Ares (Appice 2005)
- Weka-GDPM (Bogorny 2006d)

Referências

- *Tutorial on Geographic and Spatial Data Mining* - Michael May: http://www.sebd.org/2007/images/May-Tutorial-SEBD-07.pdf
- SHEKHAR, S., CHAWLA, S. Spatial databases: a tour. Upper Saddle River, NJ: Prentice Hall, 2003.
- Bogorny, V. and Shekhar S. *Tutorial on Spatial and Spatio-Temporal Data Mining* In: SBBD 2008. (http://www.inf.ufsc.br/~vania/tutorial.zip).